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FORECASTING CANADIAN RECESSIONS WITH MACROECONOMIC INDICATORS

by

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ABSTRACT

This paper examines the capacity of a variety of macroeconomic indicators in predicting recessions in Canada using a standard probit model. The predictive capacity of about fifty domestic and international economic variables is assessed for a forecast horizon of one to eight quarters and three years. The predictive capacity of each macroeconomic indicator is also evaluated in combination with another variable. The paper uses these results to propose four probit models for forecasting the probability of recessions over four different horizons. Both the in-sample and out-of-sample predictive performances of the models are assessed.

The results show that the Department of Finance index of leading indicators of economic activity is the strongest predictor of recessions for a forecast horizon of one quarter. The Bank of Canada index of nominal monetary conditions has substantial predictive capacity for the same horizon. Second, the yield curve is the variable with the highest predictive content with respect to recessions over forecast horizons of two to four quarters. The predictive power of the index of leading indicators is substantially enhanced when it is used in combination with the index of nominal monetary conditions or the German yield curve. For a forecast horizon of two quarters, the real TSE stock price index is the indicator that adds the most to the predictive capacity of the yield curve. Lastly, the German yield curve is the only indicator that adds predictive capacity to the Canadian yield curve for forecast horizons of three and four quarters.

The second part of the study illustrates the performance in predicting recessions of four probit models for each of the forecast horizons from one to four quarters. In-sample, the probit model one-quarter ahead accurately predicts the start date of all recessions in Canada since the 1960s and produces an advance warning for all of them. The results of an out-of-sample simulation show that it predicts the start date of the 1981-1982 and 1990-1991 recessions. The performance of the probit models two- to four-quarters ahead is less impressive in predicting the actual start of a recession. The three models produce, however, a warning signal for all recessions, except the 1970 recession. Finally, the probit models one- to four-quarters ahead never produce a false signal of a recession.

RÉSUMÉ

Ce document examine la capacité de divers indicateurs macroéconomiques de prévoir les récessions au Canada à l'aide d'un modèle de probabilité. La capacité de prévision d'environ 50 variables économiques nationales et internationales, considérées individuellement ou en paires, est évaluée sur des horizons prévisionnels de un à trois ans. Quatre modèles de prévision de la probabilité d'une récession sur quatre horizons différents sont retenus. La capacité de prévision des modèles est évaluée à l'intérieur et à l'extérieur de l'échantillon.

Les résultats montrent que l'indice des indicateurs avancés de l'activité économique du ministère des Finances est la variable macroéconomique qui permet le mieux de prévoir les récessions sur un horizon prévisionnel d'un trimestre. L'indice nominal des conditions monétaires de la Banque du Canada a aussi une forte capacité de prévision sur le même horizon.. La courbe de rendement est la variable qui permet le mieux de prévoir les récessions sur des horizons prévisionnels de deux à quatre trimestres. Par ailleurs, la capacité de prévision de l'indice des indicateurs avancés est sensiblement améliorée lorsqu'il est utilisé en conjonction avec l'indice nominal des conditions monétaires ou la courbe de rendement allemande. Sur un horizon prévisionnel de deux trimestres, l'indice réel du cours des actions de la Bourse de Toronto est l'indicateur qui accroît le plus la capacité de prévision de la courbe de rendement. La courbe de rendement allemande est le seul indicateur qui accroît la capacité de prévision de la courbe de rendement canadienne sur les horizons prévisionnels de trois et quatre trimestres.

La deuxième partie de l'étude illustre la capacité de prévision des récessions des quatre modèles de probabilité. À l'intérieur de l'échantillon, le modèle de probabilité un trimestre à l'avance prévoit exactement la date du début de toutes les récessions au Canada depuis les années 60 et avertit à l'avance dans tous les cas. Les résultats d'une simulation hors-échantillon montrent qu'il prévoit la date du début des récessions de 1981-1982 et de 1990-1991. La capacité des modèles de probabilité deux à quatre trimestres à l'avance est moins impressionnante pour ce qui est de prévoir la date du début d'une récession. Les trois modèles signalent cependant à l'avance toutes les récessions, sauf celle de 1970. Enfin, aucun des modèles de probabilité présentés ne donnent de faux signal d'une récession.

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1 INTRODUCTION

During the 1980s and 1990s, there were many studies done examining how much information current economic indicators contain about future real activity. For example, Muller (1992) did extensive empirical research in the early 1990s for Canada. He demonstrated that, among the monetary and credit aggregates, real M1 was the strongest predictor of future real activity in Canada. Subsequently, Cozier and Tkacz (1994) showed a strong predictive relationship between the slope of the yield curve and Canadian real activity one-year ahead.

A recent study by Estrella and Mishkin (1995b) provided empirical evidence for the United States that the former U.S. Commerce Department index of leading indicators of economic activity[1] and stock prices are the most useful predictors of recession one- or two-quarters ahead. They reported that the slope of the yield curve was the strongest predictor for forecast horizons beyond two quarters. They also looked at the performance of a few probit models in forecasting recessions since the 1960s.[2] Their models performed well, but failed to predict the 1990-1991 U.S. recession.

Our research differs from the studies of Muller (1992) and Estrella and Mishkin (1995b) in several respects. In contrast to Muller, we focus on examining the predictive capacity of economic variables in forecasting recessions rather than future growth in real activity. We also look at the predictive capacity of a wider variety of economic indicators. In contrast to Estrella and Mishkin, we investigate more extensively the problem of developing probit models to predict recessions with different forecast horizons. We examine four probit models to predict recessions for each of the forecast horizons from one to four quarters. The paper assesses their in-sample forecasting performance over the period 1962-1995 and their out-of-sample ability in forecasting the 1981-1982 and 1990-1991 recessions. The latter test will inform us better about the real time ability of the models in predicting any future recession in Canada.

The paper is organized as follows. Section 2 presents a review of previous studies on the predictive capacity of economic variables about future real activity in Canada. Section 3 is divided in two parts. The first describes the macroeconomic indicators we have chosen to examine. The second describes the empirical approach we use to assess their predictive capacity. Section 4 presents the main results, focusing on the individual variables with the highest predictive capacity for each forecast horizon. We assess for each of the forecast horizons from one to four quarters whether the addition of another variable enhances predictive performance. Drawing from the results in section 4, section 5 examines and evaluates the in-sample and out-of-sample performances of four probit models in forecasting recessions in Canada. The last section summarizes the key empirical findings of our research.

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1 Since mid-1996, the U.S. Conference Board is responsible for the U.S. index of leading indicators.

2 They used two probit models for a forecast horizon of two quarters and two for a horizon of a year. As the exogenous variable, the first model used the U.S. Department of Commerce index of leading indicators, the second used the Stock and Watson index of leading indicators for the U.S. economy, and the third used the U.S. yield curve. The last model used the U.S. yield curve and a U.S. stock price index as the exogenous variables. See also Lamy (1997) for further results on predicting U.S. recessions.

2 A REVIEW OF THE LITERATURE

Over the last 10 years, many economists have studied the capacity of a number economic indicators to predict real activity in Canada. We review the literature briefly below.

Hostland, Poloz and Storer (1988) examine the predictive capacity of alternative definitions of the monetary aggregates in relation to the future growth rate of real GDP and other indicators of aggregate demand. Using bivariate and multivariate linear regression models, they find that the rate of growth of real M1 is the most useful leading indicator of future growth in real GDP for the period 1969 to 1986. They also report that real short-term interest rates and real stock prices provide significant information with respect to future growth in real activity.

Milton (1988) extends the research of Hostand, Poloz and Storer (1988) by examining the predictive content of credit aggregates in relation to the rate of growth of nominal and real GDP and inflation. Milton (1988) uses bivariate and multivariate vector autoregressive models to examine the relationship of credit indicators to future real activity and future inflation during the 1970s and 1980s. She finds the credit aggregates, particularly residential mortgages and chartered bank business credit, to have predictive capacity for future real GDP growth. Her research reveals, however, that these two credit aggregates are both inferior to real M1 as predictors of real output growth.

The most extensive recent study on the predictive capacity of monetary and credit aggregates was published in the early 1990s by Muller (1992). He uses correlation analysis and bivariate and multivariate indicator models to investigate the predictive capacity of monetary and credit aggregates during the 1972-1989 period. Muller (1992) shows through a correlation analysis that growth in real M1 leads real GDP growth by two quarters and that the other monetary and household credit aggregates are lagging indicators of real output growth.[3] His best indicator model, whose explanatory variables are the rate of growth of real M1 lagged one and two quarters and real GDP growth lagged one quarter, explains 37 per cent of the variance of real GDP growth over the period 1972 to 1989.[4] Finally, Muller finds that his indicator model is stable during the estimation period, despite financial market innovations, and is able to predict quite well real GDP growth one-quarter ahead.

Hu (1993) examines the relationship of the slope of the yield curve to future real economic growth for Canada and other G-7 countries. He uses a simple regression model, where the growth rate of real GDP is regressed against the yield curve lagged four quarters.[5] His main result for Canada is that the yield curve is a good predictor of real economic growth a year ahead. The author also shows that the yield curve has higher predictive capacity for future real output growth than the growth rate of both real stock prices and lagged real GDP.

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3 Muller (1992) also shows that real M2, real M2+, and real M3 are leading indicators of inflation.

4 In comparison, an indicator model of real GDP growth, which was built recently by the author of this paper, explains 82 per cent of the variance of real GDP growth over the same estimation period.

5 In the Hu (1993) study, real GDP growth for the G-7 countries is expressed on a year-to-year basis.

Finally, Cozier and Tkacz (1994) examine the predictive capacity of the slope of the yield curve in relation to future real activity in Canada. They find a strong and positive relationship between the yield curve and real GDP growth one-year ahead.[6] They also assess the predictive strength of the yield curve in relation to real interest rates, real M1, real stock prices, real profits and profits as per cent of GDP, Statistics Canada's index of leading indicators, and finally the U.S. yield curve. Their empirical results show that the predictive capacity of the yield curve is largely unaffected by the addition of each of these variables. Only the level of real interest rates adds predictive capacity to that already contained in the yield curve.

3 DATA AND THE MODEL

The first part of this section describes the macroeconomic indicators we have chosen to examine. The second part presents the statistical approach we use to quantify the predictive capacity of the macroeconomic indicators with respect to recessions.

3.1 *List of macroeconomic indicators*

We evaluate the predictive capacity of a wide variety of macroeconomic indicators with respect to recessions in Canada. All the data are quarterly, seasonally adjusted[7], and expressed as a level or as a percentage change from the previous quarter.

Table 1 on pages 7 and 8 contains the list and symbols of all the macroeconomic indicators. Fiscal policy indicators are included in the list to quantify their predictive capacity in forecasting recessions. Credit indicators are not considered, because Muller (1992) found them to be strong lagging indicators of real activity. The Conference Board index of business confidence is ignored because no data are available before 1977.[8] We also look at the predictive capacity of the U.S. and German yield curves in forecasting recessions. Bernard and Gerlach (1996) found, using reference dates for recessions in Canada based on the industrial production cycle, that both the U.S. and German yield curves to be useful in predicting Canadian recessions. The yield curves for Japan, France, the U.K. and Italy are not included as foreign indicators, because data for the 1960s and most of the 1970s are not readily available.

3.2 *Description of the model*

The empirical studies reviewed in the previous section examined economic variables as predictors of real activity. They quantified predictive capacity by estimating bivariate and multivariate linear regression models. The dependant variable was most often defined as the quarter-to-quarter growth of real GDP. All the data points were used to obtain a quantitative measure of the predictive content.

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[6] The yield curve has consistently over-predicted the year-to-year growth of real GDP since about the end of the 1980s.

[7] Except for interest rates, exchange rates, and stock market variables.

[8] The survey began in the first quarter of 1977.

TABLE 1
LIST OF THE MACROECONOMIC INDICATORS

INTEREST RATE INDICATORS	
Nominal interest rates	
Three-month prime corporate paper	RCP90
Prime business	RPRIME
Three-month Treasury bills	RTB90
One- to three-years Canadian government bond	RG1TO3
Three- to five-years Canadian government bond	RG3TO5
Five- to ten-years Canadian government bond	RG5TO10
Over ten years Canadian government bond	RG10
Real interest rates (calculated with current CPI inflation)	
Three-month prime corporate paper	RRCP90
Prime business	RRRIME
Three-month Treasury bills	RRTB90
One- to three-years Canadian government bond	RRG1TO3
Three- to five-years Canadian government bond	RRG3TO5
Five- to ten-years Canadian government bond	RRG5TO10
Over ten years Canadian government bond	RRG10
INTEREST RATE SPREADS	
Over ten years bond rate minus three-month commercial paper rate	RG10-RCP90
Three-month commercial paper rate minus three-month Treasury bill rate	RCP90-RTB90
Reverse yield (over ten years bond minus stock dividend yield)	RY
Spread between Canada and U.S. long-term interest rates	SLTCAUS
Spread between Canada and U.S. short-term interest rates	SSTCAUS
MONETARY INDICATORS	
Nominal monetary aggregates	
Growth in M1	M1
Growth in M2	M2
Growth in M2+	M2+
Growth in M3	M3
Real monetary aggregates (deflated with CPI)	
Growth in real M1	RM1
Growth in real M2	RM2
Growth in real M2+	RM2+
Growth in real M3	RM3

TABLE 1 (continued)

MONETARY CONDITIONS INDEX	
Level of the index of nominal monetary conditions	MCI
Level of the index of real monetary conditions	RMCI
EXCHANGE RATES	
Growth in nominal Canada-U.S. exchange rate	PFX
Growth in real Canada-U.S. exchange rate (deflated with relative CPI inflation)	RPFX
STOCK MARKET INDICATORS	
Growth in TSE index	TSE
Growth in real TSE index (deflated with CPI)	RTSE
Dividend yield	DY
Prices/earnings ratio	PER
DOMESTIC ACTIVITY INDICATORS	
Growth in real GDP	RGDP
Growth in Statistics Canada index of leading indicators (smoothed)	SCLIS
Growth in Statistics Canada index of leading indicators (unsmoothed)	SCLI
Growth in Department of Finance index of leading indicators	FLI
Change in sales/inventory ratio	ΔSTOIR
FISCAL POLICY INDICATORS	
Change in the federal budget balance (as a percent of GDP)	ΔGBF
Change in federal government revenues (as a percent of GDP)	ΔGRF
Change in federal government spending (as a percent of GDP)	ΔGSF
CONFIDENCE INDICATORS	
Level of consumer confidence	CC
Change in consumer confidence	ΔCC
FOREIGN INDICATORS	
Growth of U.S. real GDP	USRGDP
Growth of U.S. Conference Board index of leading indicators	USLI
U.S. yield curve (10-year G-bond minus 3-month T-bill)	USYC
Growth of Dow Jones industrials stock price	DJI
Growth of S&P 500 stock price	SP500
Growth in real S&P 500 stock price (deflated with CPI)	RSP500
U.S. reverse yield (long-term bond rate minus dividend yield)	USRY
German yield curve	GERYC

The goal of our research is different. We want to quantify predictive capacity with respect to recessions. We will therefore have to use a statistical model other than the usual linear regression model. We adopt the same model as described in Estrella and Mishkin (1995b), who used a standard probit model to quantify the predictive ability in forecasting U.S. recessions.

The general specification of the probit model, which models the probability to be in a recession in quarter $t+k$ where k is the forecast horizon, is:

$$[1] \qquad P\{Y_{t+k}=1\} = F\{\beta_0 + \beta_1 X_{1,t}\} \quad \textit{where} \quad k = 1,2,3,\ldots,8 \textit{ and } 12.$$

where the dependent variable, Y_t, is a binary variable taking the value of one when the economy is in a recession and zero otherwise. The dependant variable is constructed using Statistics Canada reference dates for turning points in the business cycle.[9] We used the first quarter of 1991 as the end of the 1990-1991 recession, although no agreed date yet exists.[10] The β's are the coefficients of the model and $X_{i,t}$ are the macroeconomic indicators.

The estimation period for all probit models start in the first quarter of 1962 and ends in the fourth quarter of 1995, except for the monetary aggregates and the confidence indicators.[11] The probit models for the monetary aggregates are estimated from the second quarter of 1973, while the estimation for the confidence indicators starts in the second quarter of 1969.[12]

We use two criteria to assess the predictive capacity of the individual variables. The first criteria is the pseudo-R^2, a quantitative measure that was developed by Estrella (1995). The pseudo-R^2 is a measure of the goodness of fit of an estimated probit model.[13] As for the R^2 from a linear regression model, the value of the pseudo-R^2 lies between zero and one. A value close to zero indicates that the model has low predictive capacity for recessions, while a value closer to one means the opposite. This criteria will permit the ranking of each macroeconomic indicator in terms of their predictive capacity. The second criteria is the student t-statistic. We will apply the usual statistical tests to indicate whether the coefficient on a macroeconomic indicator is different from zero at a 5 per cent level of confidence.

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[9] Cross (1996), page 3.39. The periods of recessions are: 1970:Q1-1970:Q2, 1974:Q2-1975:Q1, 1980:Q1-1980:Q2, 1981:Q3-1982:Q4, and 1990:Q2-1991:Q1.

[10] The monthly level of real GDP at factor cost stopped contracting in March 1991.

[11] The estimation period takes account of the forecast horizon. This means that all the time series starts as late as the first quarter of 1959.

[12] No data is available before 1969:Q1 for the monetary aggregates and 1967:Q1 for the index of consumer confidence. Note that the estimation period starts later to take account of the forecast horizon. As a result, care is necessary in comparing the pseudo-R^2 values associated from the monetary aggregates and confidence variables.

[13] The pseudo-R^2 is given by $1 - (\log L_u / \log L_c)^{(-2/n) * \log L_c}$, where L_u is the likelihood value of the estimated model, L_c is the likelihood value of a probit model containing only a constant as regressor, and n the number of observations in the sample.

4 MACROECONOMIC INDICATORS AS PREDICTORS OF RECESSIONS

This section presents the results for the predictive capacity of the individual macroeconomic indicators listed in Table 1. Section 4.1 discusses the main results of estimating a probit model for each of the macroeconomic indicators. Section 4.2 reports the results of estimating two-variable probit models.

4.1 *One-variable probit models for k-quarter forecast horizon*

Table A.1 in appendix A gives the empirical results for all the macroeconomic indicators for each *k*-quarter forecast horizon. Table 2 of page 11 provides a summary of table A.1 and reports only the results for the forecast horizon one to eight quarters.[14] In table 2, the results in bold for each of the forecat horizon correspond to the macroeconomic indicator with the highest pseudo-R^2 .

4.1.1 *Predictive capacity for k = 1*

The pseudo-R^2 varies from zero to slightly less than 0.500 for a forecast horizon of one quarter. The real short and long-term interest rates, nominal monetary aggregates and exchange rate variables are among the indicators with the least predictive capacity in forecasting recessions.

The predictive capacity is highest for the Department of Finance index of leading indicators (FLI).[15] As shown by the t-statistic, the leading indicator is statistically significant in predicting recessions up to four quarters ahead. Its predictive capacity, as measured by the pseudo-R^2, however, declines rapidly after two quarters. This is consistent with its historical average lead time at the peak of the business cycle.

The leading indicator FLI has 66 per cent more predictive capacity in forecasting recessions than the Statistics Canada leading indicator (SCLIS). The pseudo-R^2 for the probit model using the growth rate of SCLIS lagged one quarter is 0.278.[16] It is also noteworthy that the leading indicator FLI has much more predictive capacity than the corresponding leading indicator for the U.S. economy. Estrella and Mishkin (1995b) reports a pseudo-R^2 of 0.236[17] for the U.S. index of leading indicators.[18] The much inferior predictive capacity is likely due in part to the fact that it contains a real stock price index as one of its components.[19] The stock prices is an indicator that has produced many false signals of recessions.

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[14] The predictive capacity when $k = 12$ is minimal. Hence, we do not discuss the results for this forecast horizon.

[15] The index of leading indicators for the Canadian economy was built by Lamy (1992). The index of leading indicators is used, along with other variables, to forecast real GDP growth one-quarter ahead. That model explains 86 per cent of the variance of real GDP growth over the 1978: Q1 to 1996:Q4 period.

[16] The pseudo-R^2 for the probit model using the current rate of growth of the Statistics Canada index of leading indicators is much higher at 0.485. This means that this leading indicator is coincident with rather than leading the business cycle peaks. Muller (1992) arrives at the same conclusion about future real GDP growth.

[17] This value is less than the pseudo-R^2 for a probit model using U.S. real GDP growth lagged one quarter.

[18] In December 1996, the U.S. Conference Board index of leading indicators was revised to include the yield curve as a component and to make other changes. Our results indicate that the revised leading indicator does not have more predictive capacity in forecasting U.S. recessions than the previous version. The results are reported in Lamy (1997).

[19] The Statistic Canada index of leading indicators also cointain a stock price as a component.

TABLE 2
SUMMARY OF THE ESTIMATION RESULTS: PROBIT MODELS FOR K-QUARTER FORECAST HORIZON

$P(R_{t+k} = 1) = F(\beta_0 + \beta_1 * X_{it})$

(1962: Q1 - 1995: Q4)

		Forecast horizon							
Variable X_i	**Statistics**	**k=1**	**k=2**	**k=3**	**k=4**	**k=5**	**k=6**	**k=7**	**k=8**
RCP90	Pseudo-R^2	0.354	0.354	0.268	0.182	0.128	0.071	0.040	0.001
	t-statistics	5.09*	4.92*	4.80*	4.34*	3.84*	3.03*	2.32*	1.62
RG1TO3	Pseudo-R^2	0.251	0.225	0.166	0.117	0.086	0.054	0.002	0.029
	t-statistics	4.71*	4.58*	4.19*	3.69*	3.26*	2.67*	2.26*	1.87
RRCP90	Pseudo-R^2	0.035	0.041	0.020	0.000	0.000	0.000	0.000	0.000
	t-statistics	2.12*	2.28*	1.60	0.89	0.80	0.21	-0.11	-0.49
RRG10	Pseudo-R^2	0.017	0.031	0.050	0.055	0.040	0.029	0.017	0.009
	t-statistics	-1.51	-1.99	-2.51*	-2.62*	-2.27*	-1.95	-1.53	-1.08
RG10-RCP90	Pseudo-R^2	0.310	**0.463**	**0.404**	**0.253**	0.174	0.083	0.033	0.006
	t-statistics	-5.08*	**-4.90***	**-5.07***	**-4.91***	-4.38*	-3.23*	-2.11*	-0.89
RM1	Pseudo-R^2	0.271	0.120	0.052	0.074	0.034	0.004	0.008	0.002
	t-statistics	-4.25*	-3.79*	-2.08*	-2.43*	-1.71	-0.58	-0.85	0.47
MCI	Pseudo-R^2	0.414	0.419	0.317	0.210	0.144	0.086	0.052	0.025
	t-statistics	4.82*	4.80*	4.81*	4.35*	3.83*	3.16*	2.53*	1.80
RMCI	Pseudo-R^2	0.000	0.034	0.071	0.050	0.081	0.048	**0.080**	**0.044**
	t-statistics	0.06	2.10*	2.96*	2.53*	3.09*	2.43*	**2.47***	**2.34***
RTSE	Pseudo-R^2	0.115	0.148	0.057	0.005	0.000	0.017	0.012	0.016
	t-statistics	-3.75*	-4.11*	-2.70*	-0.83	0.18	1.50	1.27	1.42
SCLIS	Pseudo-R^2	0.278	0.130	0.039	0.004	0.002	0.007	0.004	0.000
	t-statistics	-5.05*	-3.92*	-2.27*	-0.77	0.52	0.97	0.72	0.18
FLI	Pseudo-R^2	**0.462**	0.319	0.186	0.098	0.052	0.026	0.024	0.017
	t-statistics	**-5.33***	-5.22*	-4.46*	-3.39*	-2.43*	-1.52	-1.33	-0.70
USRGDP	Pseudo-R^2	0.216	0.091	0.043	0.022	0.004	0.001	0.011	0.015
	t-statistics	-4.72*	-3.31*	-2.35*	-1.72	-0.69	-0.40	1.22	1.39
USLI	Pseudo-R^2	0.202	0.124	0.060	0.026	0.009	0.002	0.002	0.000
	t-statistics	-4.51*	-3.89*	-2.82*	-1.87	-1.10	-0.55	-0.57	-0.20
USYC	Pseudo-R^2	0.086	0.190	0.255	0.232	**0.230**	**0.159**	0.073	0.024
	t-statistics	-3.23*	-4.29*	-4.66*	-4.55*	**-4.42***	**-3.97***	-2.95*	-1.76
RSTCAUS	Pseudo-R^2	0.165	0.153	0.063	0.021	0.004	0.004	0.007	0.007
	t-statistics	4.27*	4.03*	2.83*	1.69	0.70	-0.71	-0.97	-0.95
GERYC	Pseudo-R^2	0.127	0.172	0.188	0.187	0.155	0.086	0.024	0.000
	t-statistics	-3.92*	-4.36*	-4.41*	-4.46*	-4.16*	-3.27*	-1.82	-0.30
RGDP	Pseudo-R^2	0.150	0.034	0.019	0.012	0.000	0.003	0.005	0.009
	t-statistics	-3.90*	-2.08*	-1.59	-1.28	0.10	0.66	0.77	1.12
ΔGSF	Pseudo-R^2	0.144	0.035	0.001	0.009	0.001	0.006	0.005	0.001
	t-statistics	3.94*	2.15*	0.42	1.10	-0.34	-0.93	-0.82	-0.43
CC	Pseudo-R^2	0.280	0.129	0.030	0.005	0.000	0.007	0.010	0.027
	t-statistics	-4.41*	-3.42*	-1.75	-0.76	-0.06	0.86	1.00	1.63

Note: The (*) mean that the variable X_i is statistically different from zero at 5 per cent.

The pseudo-R^2 associated with the index of nominal monetary conditions (MCI) is equal to 0.414.[20] Compared with the leading indicator FLI, the monetary policy indicator also has substantial predictive capacity one-quarter ahead. It has much more predictive capacity than short-term interest rates and real M1. This suggests that the nominal MCI is the monetary policy indicator that would be most useful in forecasting developments in the business cycle following a change in monetary policy. Surprisingly, the index of real monetary conditions (RMCI) does not have any predictive capacity. The pseudo-R^2 is zero for $k = 1$ and below 0.100 for all other forecast horizon k.

The other indicators with relatively good predictive capacity one-quarter ahead are the yield curve, consumer confidence, and growth of U.S. real GDP among the foreign indicators. Lastly, fiscal indicators have insignificant predictive capacity for forecasting recessions.

4.1.2 *Predictive capacity for k = 2*

For a forecast horizon of two quarters, the yield curve is the indicator with the most predictive capacity for forecasting recessions. The pseudo-R^2, at 0.463, is the highest value among all the variables. Also, the yield curve has more predictive capacity two quarters ahead than a year ahead. This is a different leading relationship than it has with future growth in real activity, since Cozier and Tkacz (1994) show it is a strong predictor of real GDP growth one year ahead.

The index of nominal monetary conditions still has high predictive capacity for a forecast horizon of two quarters, with a pseudo-R^2 of 0.419. This value is only slightly below the estimated measure of goodness of fit for the yield curve probit model. Other economic variables with good forecast ability for recessions when $k = 2$ are the nominal short-term interest rates and the Department of Finance index of leading indicators. For both variables, the pseudo-R^2 is between 0.300 and 0.360. Finally, all other variables have a pseudo-R^2 generally below 0.200, which undoubtedly means that they have low predictive content.

4.1.3 *Predictive capacity for k = 3 and k = 4*

Beyond a forecast horizon of two quarters, the yield curve remains the most powerful predictor of recessions. This corroborates the findings of Estrella and Mishkin (1995b) for the U.S. economy.[21] Table 2 also shows that its predictive capacity declines rapidly with longer forecast horizons. Between a year-and-half and two-years ahead, the yield curve loses predictive ccontent with respect to recessions.

The index of nominal monetary conditions is the indicator with the second highest predictive capacity for forecast horizons of three and four quarters. The nominal short-term interest rate (RCP90), the U.S. yield curve, and the German yield curve all have good predictive capacities, but much less than the nominal MCI. Finally, real short-term and long-term interest rates, nominal and real monetary aggregates, stock market indicators, exchange rates, and confidence indicators all have very low predictive power.

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[20] The Bank of Canada developed the MCI. They constructed it with a short-term interest rate and an exchange rate. Both the first difference of the real and nominal MCI have low predictive capacity one-quarter ahead with respect to recessions. The same conclusion applies for longer forecast horizons. See Freedman (1994) for further details.

[21] For the U.S., Estrella and Mishkin (1995b) shows that the yield curve has the highest predictive content for a forecast horizon of four quarters.

Beyond a forecast horizon of four quarters, the predictive capacities of the yield curve and the index of nominal monetary conditions fall quickly. The U.S. yield curve is the best predictor with respect to recessions for forecast horizons of five and six quarters. Finally, all the macroeconomic indicators have no predictive content more than six quarters ahead, with a pseudo-R^2 generally below 0.100, in forecasting recessions.

4.1.4 *Key findings*

The main findings on the predictive capacity of the macroeconomic indicators, which are listed in table 1, in forecasting recessions are:

- For a forecast horizon of one quarter, the Department of Finance index of leading indicators is the variable with the most predictive capacity. The nominal monetary conditions index has also substantial predictive capacity and much more than any other monetary policy indicator.

- For forecast horizons of two to four quarters, the yield curve is the indicator with the highest predictive content. The nominal MCI still has high predictive capacity for the same horizon period.

- Beyond a forecast horizon of four quarters, the macroeconomic indicators have generally low predictive capacity in forecasting recessions.

4.2 *Two-variable probit models for forecast horizons of one to four quarters*

This section examines whether the addition of another variable at different lag periods will help to enhance the predictive capacity of the Department of Finance index of leading indicators and the yield curve. A variable is judged as enhancing the predictive capacity of the leading indicator or the yield curve when the coefficient associated with that variable is statistically different from zero at 5 per cent.

We estimate a probit model for each of the forecast horizons from one to four quarters, using in turn, as the second explanatory variable, one of the macroeconomic indicators of table 1. The four probit models are:

$$[2] \quad P\{Y_{t+1}=1\} = F\{\beta_0 + \beta_1 FLI_t + \beta_2 X_{i,t-l}\} \qquad \text{for } l=0,\ldots,11$$

$$[3] \quad P\{Y_{t+2}=1\} = F\{\beta_0 + \beta_1 (RG10 - RCP90)_t + \beta_2 X_{i,t-l}\} \qquad \text{for } l=0,\ldots,10$$

$$[4] \quad P\{Y_{t+3}=1\} = F\{\beta_0 + \beta_1 (RG10 - RCP90)_t + \beta_2 X_{i,t-l}\} \qquad \text{for } l=0,\ldots,9$$

$$[5] \quad P\{Y_{t+4}=1\} = F\{\beta_0 + \beta_1 (RG10 - RCP90)_t + \beta_2 X_{i,t-l}\} \qquad \text{for } l=0,\ldots,8$$

where l is the lag (in quarters)on the second variable X_i. We impose a maximum of twelve quarters between each of the forecast horizons and the number of lags on X_i to restrict the number of regressions. The variable, Y, is the recession variable, as defined before. The exogenous variables are defined in table 1 page 7 and 8. The coefficients of the models are estimated from the first quarter of 1962 to the fourth quarter of 1995. Table A.2 in appendix A gives the in-sample statistical results for [2], Table A.3 for [3], Table A.4 for [4] and Table A.5 for [5]. Tables 3 to 5 from page 15 to 17 provides a summary of the results up to a maximum of eight quarters between each of the forecast horizons and the number of lags.

4.2.1 *Two-variable probit models one-quarter ahead*

This section discusses the statistical results of equation [2]. This equation contains the Department of Finance index of leading indicators (FLI) plus another indicator as the second explanatory variable. The statistical results are compared with the results of model [1], with FLI as the unique explanatory variable.

Table 3 shows that the index of nominal monetary conditions (MCI) enhances substantially the predictive capacity of the index of leading indicators in forecasting recessions. The index of nominal monetary conditions is highly statistically significant at 5 per cent for all lags. Further, the pseudo-R^2 is much higher relative to the probit model using only the index of leading indicators (see table 2 page 11). The pseudo-R^2 increases by 33 per cent to reach a peak of 0.615 when $l = 0$. The pseudo-R^2 diminishes with longer lags.

Surprisingly, the German yield curve (GERYC) is strongly significant for $l = 1, 2, ..., 6$. The pseudo-R^2 reaches a peak of 0.629 when $l = 3$. As with the MCI variable, the German yield curve adds substantial predictive capacity to the Department of Finance index of leading indicators. The pseudo-R^2 increases strongly when this variable is included in the probit model. The result for the influence of the German yield curve is consistent with the study of Bernard and Gerlach (1996). They showed that the German yield curve spread helps greatly in forecasting recessions in Canada when combined with another variable.[22]

The inclusion of the U.S. yield curve (USYC) adds substantial predictive capacity in forecasting recessions, but only for the lags 4, 5 and 6. The inclusion of this variable increases the pseudo-R^2 by 17 per cent, which is much less than it was for both the index of nominal monetary conditions and German yield curve. This means that the U.S. yield curve adds much less information than both of the two variables in predicting recessions. The result with respect to the German yield curve is surprising because one would expect the U.S. yield curve, which is often considered as an indicator of monetary policy, to have a more important influence on business cycles in Canada. The U.S. is by far the Canada's most important trade partner.

Table 3 shows that the rate of growth of the real TSE stock price index (RTSE) is useful in forecasting recessions one-quarter ahead. The RTSE variable is strongly significant for $l = 1$ with a t-statistic of 3.21. The addition of that variable helps to enhance the predictive capacity of the Finance index of leading indicators -- the pseudo-R^2 increases by 28 per cent to 0.592. The fit of the model, however, deteriorates rapidly with longer lags on RTSE. That variable is no longer different from zero at 5 per cent when $l > 2$.

Other indicators that provide some additional predictive capacity in forecasting recessions are: the nominal short-term interest rate (RCP90) (for $l = 0$ to 2 and 4), the yield curve (for $l = 1$ and 4), the short-term interest rate spread (for $l = 3$), the rate of growth of real M1 ($l = 0$), the change in federal government spending as a share of GDP (for $l = 0$ and 3), and the level of the consumer confidence index ($l = 1$ and 2). For all these variables, however, the improvement in the goodness of fit is much less important.

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22 As noted earlier, Bernard and Gerlach (1996) have used reference dates for recessions in Canada based on the industrial production cycle. It is noteworthy that Plosser and Rouwenhorst (1994) concluded that "...foreign term structures often have remarkable predictive content for domestic real economic growth rates".

TABLE 3
SUMMARY OF THE ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS
ONE-QUARTER AHEAD

$P(Y_{t+1} = 1) = F(\beta_0 + \beta_1 * FLI_t + \beta_2 * X_{i,t-l})$

(1962: Q1 - 1995: Q4)

		Lag *l*							
Variable X_i	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**
RCP90	Pseudo-R^2	0.516	0.516	0.504	0.500	0.504	0.493	0.486	0.479
	t-statistics	2.35*	2.26*	2.04*	1.94	2.07*	1.85	1.63	1.37
RG10	Pseudo-R^2	0.511	0.485	0.487	0.489	0.489	0.484	0.495	0.475
	t-statistics	2.17*	1.55	1.61	1.67	1.67	1.53	1.30	1.19
RRCP90	Pseudo-R^2	0.468	0.470	0.471	0.468	0.463	0.463	0.463	0.463
	t-statistics	-0.81	-0.91	-0.99	-0.79	0.26	0.19	0.12	0.15
RRG10	Pseudo-R^2	0.477	0.498	0.492	0.490	0.474	0.471	0.470	0.464
	t-statistics	-1.23	-1.85	-1.71	-1.69	-1.12	-1.00	-0.95	-0.44
RG10-RCP90	Pseudo-R^2	0.473	0.529	0.496	0.486	0.503	0.486	0.480	0.470
	t-statistics	-1.12	-2.42*	-1.82	-1.59	-2.10*	-1.63	-1.41	-0.95
RCP90-RTB90	Pseudo-R^2	0.470	0.464	0.463	0.513	0.486	0.476	0.471	0.468
	t-statistics	0.93	-0.31	-0.00	2.31*	1.33	0.92	0.66	-0.18
RM1	Pseudo-R^2	0.521	0.554	0.504	0.552	0.541	0.505	0.526	0.504
	t-statistics	-1.24	-2.00*	0.32	-1.86	-1.71	0.49	-1.36	0.39
MCI	Pseudo-R^2	0.615	0.609	0.582	0.573	0.583	0.580	0.579	0.556
	t-statistics	3.09*	3.06*	2.97*	2.87*	2.90*	3.04*	3.00*	2.69*
RMCI	Pseudo-R^2	0.477	0.478	0.480	0.488	0.545	0.545	0.533	0.524
	t-statistics	1.22	1.28	1.31	1.55	2.33*	2.39*	2.33*	2.28*
RTSE	Pseudo-R^2	0.485	0.592	0.508	0.489	0.478	0.463	0.465	0.463
	t-statistics	-1.61	-3.21*	-2.21*	-1.72	1.32	0.16	0.58	0.32
USRGDP	Pseudo-R^2	0.484	0.484	0.503	0.514	0.467	0.463	0.464	0.476
	t-statistics	-1.58	-1.51	-2.04*	-2.27*	-0.74	-0.27	0.49	1.23
USYC	Pseudo-R^2	0.463	0.468	0.487	0.489	0.542	0.532	0.495	0.489
	t-statistics	-0.17	-0.78	-1.61	-1.68	-2.60*	-2.52*	-2.08*	-1.65
GERYC	Pseudo-R^2	0.493	0.573	0.586	0.629	0.623	0.581	0.513	0.479
	t-statistics	-1.87	-3.06*	-3.18*	-3.34*	-3.21*	-3.21*	-2.35*	-1.37
RGDP	Pseudo-R^2	0.470	0.462	0.479	0.505	0.463	0.467	0.466	0.475
	t-statistics	-0.93	0.01	-1.35	-2.12	-0.11	0.73	0.61	1.17
ΔGBF	Pseudo-R^2	0.478	0.462	0.471	0.526	0.475	0.474	0.464	0.470
	t-statistics	-1.29	-0.08	0.96	-2.42*	1.16	1.13	0.42	0.91
ΔGSF	Pseudo-R^2	0.541	0.471	0.462	0.536	0.463	0.462	0.463	0.465
	t-statistics	2.73*	0.98	-0.06	2.62*	0.25	-0.01	0.15	0.59
CC	Pseudo-R^2	0.570	0.558	0.533	0.552	0.547	0.519	0.513	0.512
	t-statistics	-2.25*	-2.05*	-1.43	-1.92	-1.82	-0.88	-0.73	0.37

Note: The (*) mean that X_i is statistically different from zero at 5 per cent The value of the t-statistics corresponds to the estimated coefficient associated with the second variable $X_{i,t-l}$

TABLE 4
SUMMARY OF THE ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS
TWO-QUARTERS AHEAD

$P(R_{t+2}=1) = F(\beta_0 + \beta_1 * (RG10_t - RCP90_t) + \beta_2 * X_{i,t-l})$

(1962: Q1 - 1995: Q4)

		Lag *l*							
Variable X_i	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**
RCP90	Pseudo-R^2	0.507	0.495	0.499	0.498	0.482	0.475	0.468	
	t-statistics	1.76	1.84	1.94	1.92	1.49	1.19	0.75	
RG10	Pseudo-R^2	0.493	0.484	0.489	0.481	0.472	0.472	0.471	
	t-statistics	1.76	1.52	1.65	1.42	1.05	1.01	0.97	
RRCP90	Pseudo-R^2	0.467	0.464	0.463	0.464	0.463	0.463	0.465	
	t-statistics	-0.65	-0.40	0.01	0.36	-0.00	-0.24	-0.48	
RRG10	Pseudo-R^2	0.467	0.475	0.473	0.474	0.477	0.471	0.466	
	t-statistics	-0.65	-1.17	-1.07	-1.11	-1.22	-0.96	-0.57	
RM1	Pseudo-R^2	0.565	0.538	0.573	0.562	0.533	0.530	0.537	
	t-statistics	-1.66	-0.84	-1.78	-1.59	-0.56	-0.17	0.78	
MCI	Pseudo-R^2	0.541	0.540	0.543	0.550	0.530	0.529	0.513	
	t-statistics	2.56*	2.56*	2.68*	2.74*	2.55*	2.47*	2.20*	
RMCI	Pseudo-R^2	0.473	0.481	0.501	0.528	0.516	0.511	0.504	
	t-statistics	1.03	1.33	1.78	2.23*	2.15*	2.12*	1.97	
RTSE	Pseudo-R^2	0.579	0.543	0.477	0.473	0.464	0.464	0.471	
	t-statistics	-3.10*	-2.62*	-1.25	-1.08	0.41	0.40	0.96	
USRGDP	Pseudo-R^2	0.513	0.501	0.481	0.466	0.463	0.495	0.463	
	t-statistics	-2.25*	-1.95	-1.43	-0.60	0.14	1.80	0.16	
USYC	Pseudo-R^2	0.483	0.467	0.506	0.566	0.553	0.504	0.475	
	t-statistics	0.26	-0.69	-2.05*	-2.80*	-2.76*	-1.98*	-1.13	
RSP500	Pseudo-R^2	0.555	0.503	0.506	0.488	0.466	0.487	0.491	
	t-statistics	-2.68*	-2.03*	-2.05	-1.66	0.55	1.56	1.70	
GERYC	Pseudo-R^2	0.496	0.519	0.543	0.565	0.517	0.497	0.484	
	t-statistics	-1.89	-2.33*	-2.74*	-2.97*	-2.38*	-1.98*	-1.56	
ΔGSF	Pseudo-R^2	0.474	0.464	0.529	0.467	0.526	0.468	0.469	
	t-statistics	1.15	0.29	2.42*	0.72	-1.11	-0.79	0.83	

Note: The (*) mean that X_i is statistically different from zero at 5 per cent. The value of the t-statistics corresponds to the estimated coefficient associated with the second variable $X_{i,t-l}$

TABLE 5
SUMMARY OF THE ESTIMATION RESULTS:
TWO-VARIABLE PROBIT MODELS THREE- AND FOUR-QUARTERS AHEAD

$P(R_{t+k} = 1) = F(\beta_0 + \beta_1 * (RG10_t - RCP90_t) + \beta_2 * X_{i,t-l}), \quad k = 3, 4$

(1962: Q1 - 1995: Q4)

		Lag *l*							
Variable X_i	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**
		Probit models three-quarters ahead							
RM1	Pseudo-R^2	0.505	0.506	0.488	0.488	0.495	0.532		
	t-statistics	1.27	-1.27	-0.44	0.47	-0.85	-1.82		
MCI	Pseudo-R^2	0.435	0.423	0.432	0.427	0.425	0.418		
	t-statistics	1.80	1.44	1.73	1.61	1.55	1.29		
USYC	Pseudo-R^2	0.417	0.409	0.449	0.439	0.415	0.404		
	t-statistics	-1.20	-0.75	-2.08*	-1.88	-1.10	-0.20		
GERYC	Pseudo-R^2	0.453	0.469	0.465	0.434	0.407	0.404		
	t-statistics	-2.27*	-2.58*	-2.51*	-1.85	-0.60	0.03		
		Probit models four-quarters ahead							
RM1	Pseudo-R^2	0.319	0.318	0.335	0.318	0.336			
	t-statistics	0.33	-0.15	1.20	0.15	1.25			
MCI	Pseudo-R^2	0.274	0.267	0.264	0.263	0.258			
	t-statistics	1.57	1.30	1.17	1.12	0.77			
USYC	Pseudo-R^2	0.289	0.287	0.285	0.260	0.253			
	t-statistics	-2.00*	-1.94	-1.89	-0.90	0.07			
GERYC	Pseudo-R^2	0.340	0.325	0.282	0.256	0.256			
	t-statistics	-3.06*	-2.83*	-1.89	-0.62	0.67			

Note: The (*) mean that X_i is statistically different from zero at 5 per cent. The value of the t-statistics corresponds to the estimated coefficient associated with the variable $X_{i,t-l}$

4.2.2 *Two-variable probit models two-quarters ahead*

As demonstrated in section 4.1.2, the yield curve is the individual variable with the most predictive capacity in forecasting recessions over a forecast horizon of two quarters. Can its value be enhanced by another variable? To explore this issue, we estimate the model [3], which contains another indicator as the second explanatory variable, its first explanatory variable being, of course, the yield curve. This section presents the statistical results of estimating model [3]. The findings are compared with the statistical results of model [1], which contains only the yield curve. The results of model [3] are presented in table 4 page 16.

Table 4 reveals that the rate of growth of real TSE stock price index is the variable that most enhances the predictive capacity of the yield curve for a forecast horizon of two quarters.[23] With the real TSE stock price index, the pseudo-R^2 increases strongly by 25 per cent to 0.579. This suggests clearly that a stock price provides additional predictive capacity.

The U.S. and German yield curves and the index of nominal monetary conditions (MCI) also add predictive capacity in forecasting recessions. The use of each of these two variables in the probit model [3] increases substantially the goodness of fit, as measured by the pseudo-R^2. Other macroeconomic indicators that enhance, but to a much lesser extent, the predictive capacity of the yield curve are the index of real monetary conditions, fiscal indicators, U.S. real GDP growth, and the growth of real S&P500 stock price index. All other macroeconomic indicators do not perform well. The t-statistics are generally well below the critical level at 5 per cent.

4.2.3 *Two-variable probit models three- and four-quarters ahead*

This section reports the statistical results of using the same strategy as in the previous two subsections for forecast horizons of three and four quarters. The yield curve is the first explanatory variable of the probit models three and four quarters ahead. Remember that the yield curve was found to be the individual variable with the most predictive capacity in forecasting recessions for a forecast horizon beyond half a year. Table 5 page 17 gives a summary of the statistical results for the probit models [4] and [5].

For the forecast horizon of three and four quarters, the German yield curve strongly enhances the predictive capacity of the Canadian yield curve toward recessions. The inclusion of the German yield curve boosts the pseudo-R^2 by about 15 per cent. The U.S. yield curve also adds useful predictive capacity, but to a lesser extent.[24] Finally, the index of nominal monetary conditions (MCI) no longer enhances the predictive capacity of the yield curve for a forecast horizon beyond two quarters. Finally, all other variables are completely dominated by the strong leading relationship of the yield curve in relation to recession periods (see tables A.4 and A.5 in appendix A). For all of them, the estimated coefficient has the wrong sign or their t-statistics are generally around zero.

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[23] Estrella and Mishkin (1995b) also found that stock prices enhance the predictive capacity of the U.S. yield curve with respect to recessions. Muller (1992) found the growth of real TSE stock price index to have predictive value in relation to future growth in real GDP.

[24] Note that the U.S. yield curve is much less statistically significant at 5 per cent.

4.2.4 *Key findings*

This section has examined whether a domestic or foreign macroeconomic indicator would enhance the predictive capacity of the Finance index of leading indicators and the yield curve in forecasting recessions. Our key findings are:

- For a forecast horizon of one quarter, the index of nominal monetary conditions and the German yield curve are the two indicators that most enhance the predictive capacity of the Department of Finance index of leading indicators. The gain in predictive power is very substantial.

- For a forecast horizon of two quarters, the real TSE stock price index is the indicator that adds the most to the predictive capacity of the yield curve. Again, the improvement in predictive capacity is substantial. The index of nominal monetary conditions and the U.S. and German yield curves also enhance the predictive capacity of the yield curve.

- For forecast horizons of three and four quarters, the German yield curve adds predictive capacity to the Canadian yield curve.

5 FORECASTING RECESSIONS IN CANADA

This section presents the predictive capacity of four probit models in forecasting recessions in Canada up to four quarters ahead. The models were chosen from the results of the previous section. The section is divided in three parts. The first reports the statistical results of estimating each probit model. The second looks at the in-sample performance of the models in forecasting recessions from 1962 to 1995. The third examines the out-of-sample performance of the models in predicting the 1981-1982 and 1990-1991 recessions.

5.1 *Estimation results*

Table 7 on next page presents the statistical results for the four probit models. The coefficients of the models are estimated using data from the first quarter of 1962 to the fourth quarter of 1995. The numbers in parentheses are the t-statistics for the estimated coefficients. We also report the pseudo-R^2 -- the measure of goodness of fit.

The first equation of table 7 models the probability of a recession one-quarter ahead as a function of the rate of growth of the Department of Finance index of leading indicators (FLI), the level of the index of nominal monetary conditions (MCI), and the rate of growth of the real TSE stock price index (RTSE). The empirical research has indicated that the variable RTSE was adding useful information not contained in FLI and MCI. The estimation results for the probit model one-quarter ahead indicate that the explanatory variables are statistically different from zero at a 5 per cent level of confidence. The fit of the model, as measured by the pseudo-R^2, is high at 0.770.[23]

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[23] In comparison, the highest pseudo-R^2 obtained by Estrella and Mishkin (1995b) with a two-variable U.S. probit model for a forecast horizon of one quarter was 0.43.

TABLE 7
ESTIMATION RESULTS OF THE PROBIT MODELS FOR EACH OF THE FORECAST HORIZONS FROM ONE TO FOUR QUARTERS
(1962 Q1 - 1995 Q4)

Probit model one-quarter ahead:

$$[61] \quad P[Y_{t+1}] = F(\underset{(-3.03)}{-9.00} - \underset{(-2.97)}{0.91} * FLI_t + \underset{(2.60)}{0.66} * MCI_t - \underset{(-2.67)}{0.21} * RTSE_{t-1})$$

$$Pseudo\ R^2 = 0.770$$

Probit model two-quarters ahead:

$$[7] \quad P[Y_{t+2}] = F(\underset{(-4.87)}{-2.22} - \underset{(-4.26)}{1.18} * (RG10_t - RCP90_t) - \underset{(-3.10)}{0.12} * RTSE_t)$$

$$Pseudo\ R^2 = 0.579$$

Probit model three-quarters ahead:

$$[8] \quad P[Y_{t+3}] = F(\underset{(-4.71)}{-1.23} - \underset{(-4.26)}{0.70} * (RG10_t - RCP90_t) - \underset{(-2.58)}{0.31} * GERYC_{t-1})$$

$$Pseudo\ R^2 = 0.469$$

Probit model four-quarters ahead:

$$[9] \quad P[Y_{t+4}] = F(\underset{(-5.42)}{-1.03} - \underset{(-3.84)}{0.45} * (RG10_t - RCP90_t) - \underset{(-3.06)}{0.32} * GERYC_{t-1})$$

$$Pseudo\ R^2 = 0.340$$

The probability of a recession two-quarters ahead is determined by both the yield curve (RG10-RCP90) and the rate of growth of the real TSE stock price index (RTSE).[26] The estimated coefficients are again statistically significant at 5 per cent. The pseudo-R^2 remains high at 0.579.[27]

The last two probit models, which forecast the probability of a recession three and then four quarters ahead, contain the Canadian yield curve (RG10-RCP90) and German yield curve (GERYC). Again, as with the other models, the estimated coefficients are significant statistically. However, the measure of fit drops to 0.469 for the probit model three quarters ahead and to 0.340 for four quarters ahead.[28]

5.2 *In-sample forecasting performance*

The assessment of the reliability of the probit models in forecasting recessions is not as straightforward as evaluating the ability of a model in predicting growth of a macroeconomic indicator, such as real GDP. The evaluation of the probit models is obviously more difficult, because the probabilities provided by them cannot be observed. So, we cannot compare the forecast probabilities with actual data.

We suppose that a probit model predicts a recession when the forecast probability is equal or above 0.5, a rule which is often used in the literature as the threshold level to predict a cyclical downturn. Using that rule, the performance of the four probit models in predicting recessions are assessed with respect to the following criteria: the ability to predict the actual start date of a recession, the ability to provide a warning signal of an impending recession (even if it does not predict the exact start date), and the number of false signals of a recession.

The ability to predict a recession is evaluated by comparing the period in which the forecast probability of a recession corresponds to and the actual start date of a recession. There are three possibilities. First, a probit model predicts a recession with a lead if the forecast probability of a recession occurs before the its actual start date. Second, a probit model predicts a recession with a lag if the forecast probability of a recession occurs after its actual start date. Third, a probit model predicts a recession with no lead or no lag if the forecast probability of a recession corresponds to its actual start date. The warning signal refers to the ability of a probit model to warn of a recession before it occurs. The warning signal lead is defined as the number of quarters between the period in which a probit model forecasts a recession and the recession's actual start date. Lastly, a probit model produces a false signal when the prediction of a recession is not followed by an actual recession

Table 8 below gives the performance of the four probit models in forecasting recessions over the 1962-1995 period. Chart 1 page 25 plots the in-sample forecast probabilities for each forecast horizon for the same period.

TABLE 8

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[26] We were unsuccessful to find a third statistically significant exogenous variable among the macroeconomic indicators in table 1. It is also the case for the probit models three- and four-quarters ahead.

[27] The highest pseudo-R^2 obtained by Estrella and Mishkin (1995b) with a two-variable U.S. probit model for a forecast horizon of two quarters was 0.358.

[28] The highest pseudo-R^2 obtained by Estrella and Mishkin (1995b) with a two-variable U.S. probit model was 0.331 for a forecast horizon of three quarters and 0.314 for a forecast horizon of four quarters.

PERFORMANCE OF THE PROBIT MODELS IN PREDICTING CANADIAN RECESSIONS

	Lead or lag in predicting the start of a recession (in quarters)			
Recessions	**1-quarter ahead**	**2-quarters ahead**	**3-quarters ahead**	**4-quarters ahead**
1970	0 (-1)	No signal	No signal	No signal
1974-1975	0 (-1)	0 (-2)	0 (-3)	+1 (-3)
1980	0 (-1)	+1 (-1)	+2 (-1)	+3 (-1)
1981-1982				
- in sample	0 (-1)	0 (-2)	0 (-3)	+2 (-2)
- **out-of-sample**	0 (-1)	0 (-2)	0 (-3)	+2 (-2)
1990-1991:				
- in-sample	0 (-1)	-2 (-4)	-1 (-4)	0 (-4)
- **out-of-sample**	0 (-1)	-2 (-4)	-1 (-4)	+1 (-3)
In-sample average lead or lag	0 (-1)	-¼ (-2¼) †	+¼ (-2¾) †	+1½ (-2½) †
Number of correct signals	5/5	2/5	2/5	1/5
Number of warning signals	5/5	4/5	4/5	4/5
Number of false signals	0	0	0	0

Note: The sign "-" indicates a lead and "+" a lag. The lead or lag is calculated with the 50 per cent probability rule. The lead or lag time is the difference in quarters between the period in which the forecast probability of a recession corresponds to and the actual start date of a recession. The number between parentheses is the warning lead or lag in predicting the start date of a recession. The warning signal lead is the number of quarters between the period in which the forecast probability of a recession is computed and its actual start date. For example, suppose that the probit models for forecast horizons of one to four quarters would have predicted accurately the start of the 1990-1991 recession. Then, the warning lead would have been one quarter for the probit model one-quarter ahead, two quarters for the probit model two-quarters ahead, three quarters for the probit model three-quarters ahead, and four quarters for the probit models four-quarters ahead.

†Average over four recessions.

The in-sample results from table 8 shows that the one-quarter ahead probit model correctly forecasts the actual start of all recessions since early 1960s. The prediction of a recession is, without doubt, very clear (see panel A of chart 1). Notably, the forecast probabilities show up quite well between the 1980 and 1981-1982 recessions, despite their proximity. The forecast probabilities fall very quickly to slightly above zero at the end of the 1980 recession and remain at about that level for a few quarters.

The performance of the probit models two- to four-quarters ahead is less impressive. The probit models two- and three-quarters ahead predict the actual start of two of the five recessions, the 1974-1975 and 1981-1982 recessions. The same models predict the 1990 recession with a lag of at most two quarters and the 1990-1991 recession with a lead of at most two quarters. The probit model four-quarters ahead predicts the actual start date of the 1990-1991 recession and with a lag of at most three quarters for all other recessions. Lastly, the probit models two- to four-quarters ahead missed the 1970 recessions (see also panel B to D of chart 1).

Table 8 also reports between parentheses the warning in quarters that the probit models give for each recession. All the four probit models were successful in providing a warning signals for all recessions since the 1960s. The average warning varies between one and three quarters. Lastly, the probit models succeed in producing no false signals.

In summary, we show first that the probit model one-quarter ahead is reliable (in-sample) in forecasting the actual start date of recessions in Canada over the last 35 years. Second, the four probit models were successful in producing a warning signal of a recession, with no false signals. Third, forecast probabilities produced by the models are fairly smooth -- a desirable quality. Note also that the probit model one-quarter ahead was successful in forecasting the start of a recovery in real activity when the economy was in a recession (see table B.1 in appendix B page 46).

5.3 *Out-of-sample forecasting performance*

In this section, we examine the out-of-sample performance of the four probit models in forecasting the 1981-1982 and 1990-1991 recessions.[29] This is the most informative and useful test to gauge of the real time ability of the models in determining the likelihood of any future recession in Canada.

We conducted recursive forecasts based on a rolling regression technique to assess the out-of-sample forecasting capacity of the probit models. The out-of-sample forecasting capacity is assessed from the start of 1981 through the end of 1995. The following describes the technique we use. First, the coefficients of each probit model are estimated from the first quarter of 1962 to the fourth quarter of 1980. The estimated coefficients of each probit model are used to compute forecast probabilities for the first quarter of 1981 for forecast horizons of one to four quarters. We then increased the estimation period by one quarter and produced another set of forecast probabilities for each k quarter ahead. This rolling procedure is repeated until the fourth quarter of 1995, the end of the sample period. Chart 2 on page 26 plots the out-of-sample forecast probability for each probit model. We also plot the in-sample forecast probabilities for comparison.

Consider first the out-of-sample results for the probit model one-quarter ahead. Panel A of chart 2 shows the forecast probabilities, along with the in-sample probabilities, inferred by the one-quarter ahead

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[29] We restricted the out-of-sample period to the 1980s and 1990s because there were only five recession periods over the last three decades. We have to have a sufficient number of recession periods to get reliable coefficient estimates for the probit models.

probit model. We find that the out-of-sample probabilities are similar to the in-sample ones during the 1980s and 1990s. Out-of-sample, the one-quarter ahead probit model predicts accurately the actual start of the 1981-1982 and 1990-1991 recessions. The model also performed well during the subsequent recoveries, giving no false signals of a recession.

Panel B of chart 2 illustrates the out-of-sample performance of the probit model two quarters ahead. Again, we see that both the out-of-sample and in-sample forecast probabilities are similar during the 1981-1995 period. The model produces a strong signal of a recession for the last two downturns. The probit model two-quarters ahead predicts accurately the actual start of the 1981-1982 recession. Again, the probit models two- and three-quarters ahead produce a warning signal of an impending recession in 1981 and 1989.

The third chart, panel C, shows the out-of-sample performance of the probit model three- quarters ahead. Like the previous model, it accurately predicts the 1981-1982 recession. Panel D gives the forecasting probabilities computed with the probit model four quarters ahead. That model accurately predicts the start of the last recession, but not the 1981-1982 recession. Despite their lack of reliability in forecasting the actual start date of recessions, the two models produce warning signals for the last four recessions.

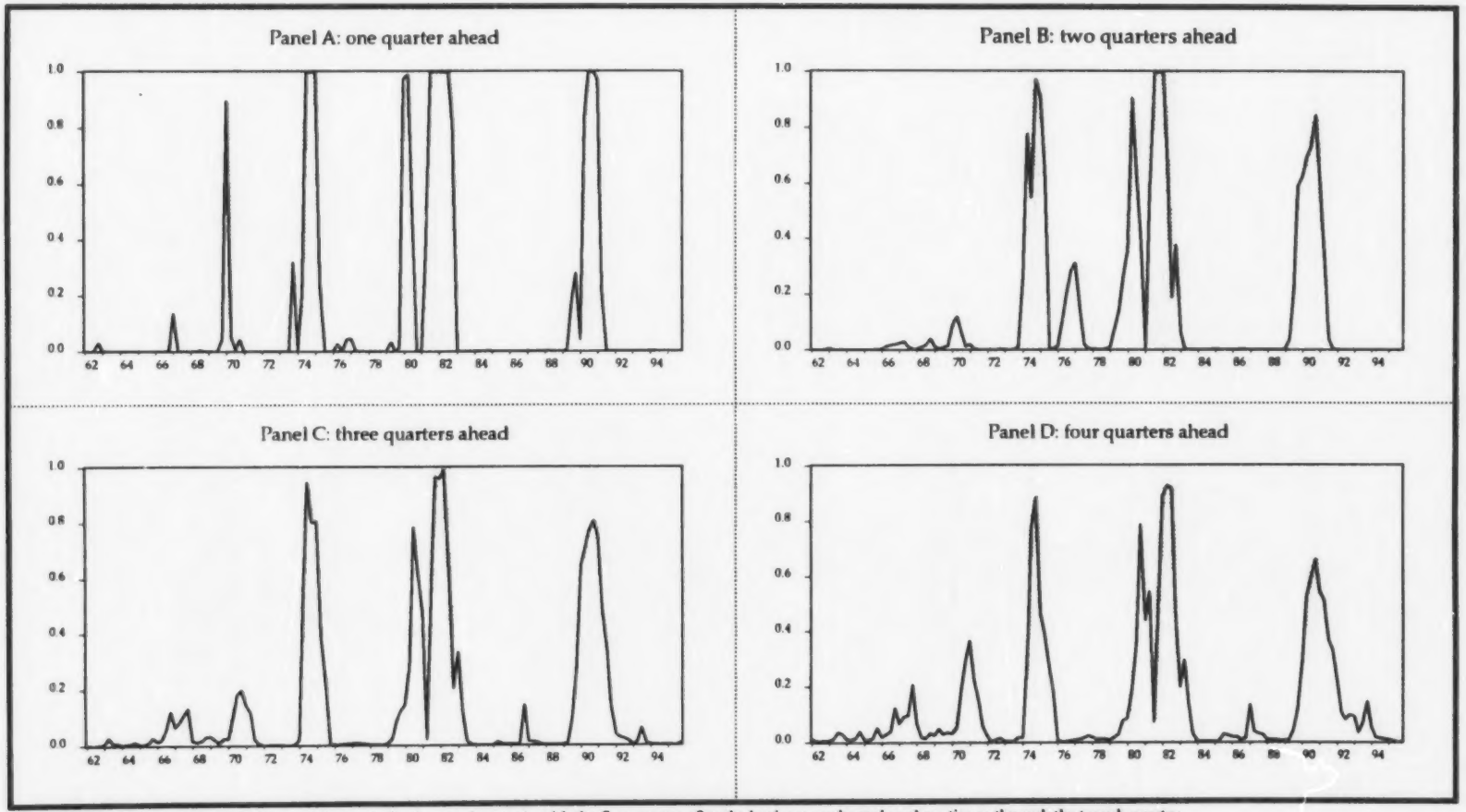
5.4 *Key results*

The analysis of the in-sample performance of the probit models in predicting Canadian recessions over the last three decades show that:

- The probit model one-quarter ahead is accurate in predicting the actual start of all recessions;
- The probit models one- to four-quarters produce a warning signal for all recessions. The average warning lead time varies between one and three quarters.
- The probit models give no false signals.

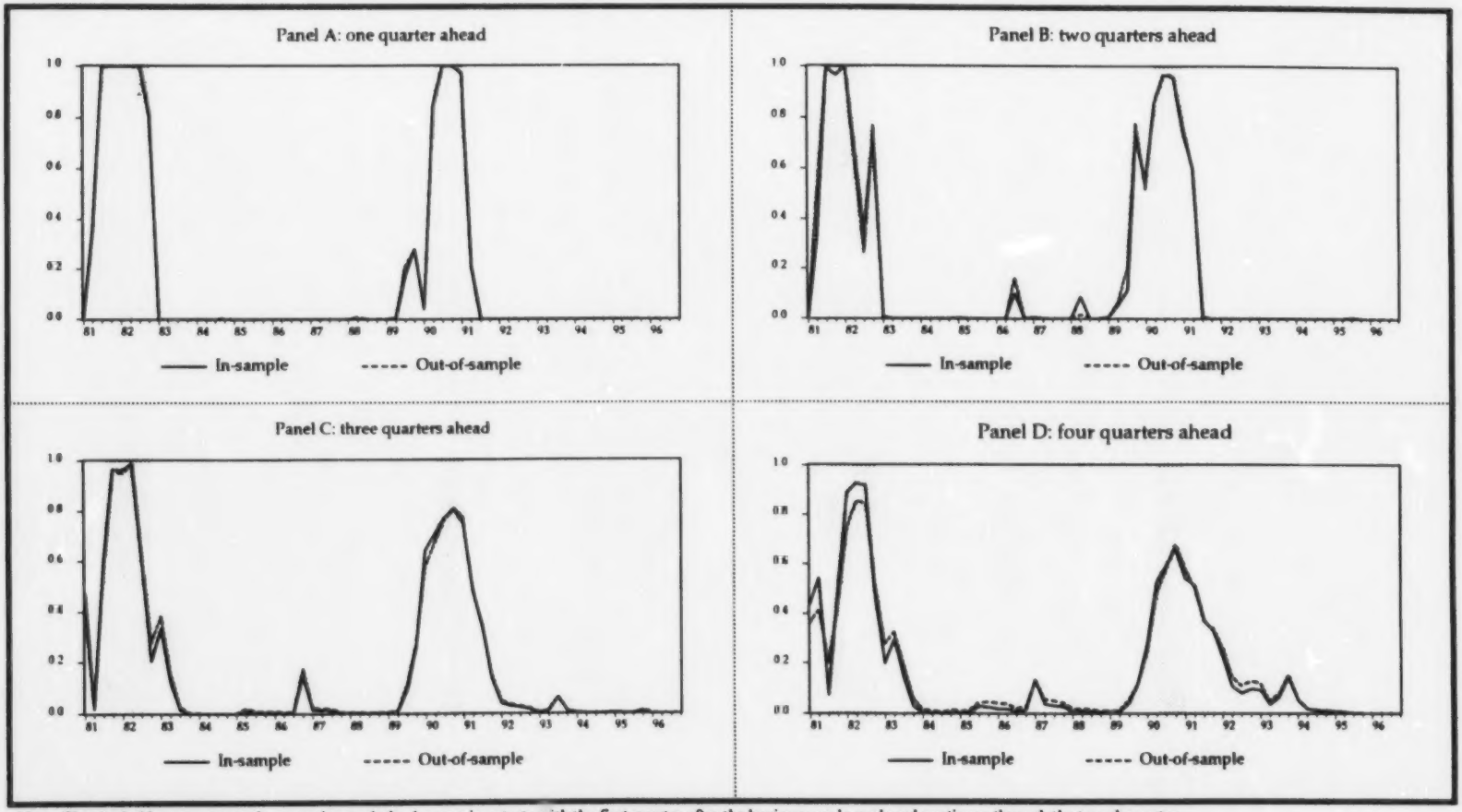
The results from the out-of-sample simulation show that the probit models one-quarter ahead predicted the actual start of the 1981-1982 and 1990-1991 recessions. Furthemore, all four probit models produce a warning signal for the 1981-1982 and 1990-1991 recessions.

CHART 1
IN-SAMPLE FORECAST PROBABILITIES FOR EACH OF THE FORECAST HORIZONS FROM ONE TO FOUR QUARTERS



Note: The shaded bars represent the recession periods. A recession starts with the first quarter after the business cycle peak and continues through the trough quarter.

CHART 2
OUT-OF-SAMPLE FORECAST PROBABILITIES FOR EACH OF THE FORECAST HORIZONS FROM ONE TO FOUR QUARTERS



Note: The shaded bars represent the recession periods. A recession starts with the first quarter after the business cycle peak and continues through the trough quarter.

6. CONCLUSION

This paper has examined the predictive capacity of a variety of macroeconomic indicators in forecasting recessions in Canada. We have also assessed the performance of four probit models in predicting recessions with forecast horizons of one to four quarters ahead.

The empirical results showed that among the macroeconomic indicators that we have examined the Department of Finance index of leading indicators of economic activity is the variable with the most predictive capacity with respect to recessions for a forecast horizon of one quarter. We found the index of nominal monetary conditions to also have significant predictive capacity one-quarter ahead. Among the monetary policy indicators, the index of nominal monetary conditions is the best predictor for all forecast horizons. For forecast horizons of two to four quarters, the yield curve has the highest predictive capacity. Most of all the other macroeconomic indicators had low predictive capacity beyond a forecast horizon of two quarters.

The predictive capacity of both the Department of Finance index of leading indicators and the yield curve is substantially enhanced when combined with another variable. For a forecast horizon of one quarter, the index of nominal monetary conditions is the indicator that most enhances the predictive capacity of the index of leading indicators. The index of nominal monetary conditions adds much more predictive capacity than the yield curve, real M1, and interest rates. For a forecast horizon of two quarters, the real TSE stock price index contains substantial information about future recessions that is not contained in the yield curve. Real stock prices outperform other variables, such as the nominal monetary conditions index and the U.S. yield curve. Beyond a forecast horizon of two quarters, only the U.S. and German yield curves add predictive capacity to the Canadian yield curve.

We have examined four probit models to predict recessions for forecast horizons of one to four quarters. In-sample, the probit model one-quarter ahead accurately predicted the actual start date of all recessions in Canada since the 1960s. An out-of-sample simulation showed that the probit model one-quarter ahead predicts the actual start date of the 1981-1982 and the 1990-1991 recessions. The performance of probit models two- to four-quarters ahead was less impressive. The probit models one- to four-quarters ahead never produced false signals of a recession and gave a warning signal of an impending recessions for all cyclical downturns since 1960s, except for the 1970 recession for the probit model two- to four-quarters ahead.

Our research has demonstrated that the probit models could provide useful information to better anticipate business cycle developments in Canada. Furthermore, such models can help in determining when a recovery in real activity might begin if the economy is already in a recession.

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APPENDIX A

TABLE A.1
ESTIMATION RESULTS: ONE-VARIABLE PROBIT MODELS K-QUARTERS AHEAD
$P(R_{t+k} = 1) = F(\beta_0 + \beta_1 * X_{it})$
(1962: Q1 - 1995: Q4)

		Forecast Horizon								
Variable - X_t	**Statistics**	**k=1**	**k=2**	**k=3**	**k=4**	**k=5**	**k=6**	**k=7**	**k=8**	**k=12**
RCP90	Pseudo-R^2	0.354	0.354	0.268	0.182	0.128	0.071	0.040	0.001	0.000
	t-statistics	5.09*	4.92*	4.80*	4.34*	3.84*	3.03*	2.32*	1.62	-0.14
RPRIME	Pseudo-R^2	0.306	0.286	0.215	0.151	0.106	0.061	0.035	0.015	0.000
	t-statistics	5.05*	4.92*	4.64*	4.13*	3.61*	2.84*	2.18*	1.44	-0.09
RTB90	Pseudo-R^2	0.256	0.255	0.200	0.146	0.110	0.069	0.045	0.029	0.000
	t-statistics	4.83*	4.75*	4.44*	3.94*	3.47*	2.70*	2.01*	1.27	-0.56
RG1TO3	Pseudo-R^2	0.251	0.225	0.166	0.117	0.086	0.054	0.002	0.029	0.000
	t-statistics	4.71*	4.58*	4.19*	3.69*	3.26*	2.67*	2.26*	1.87	0.10
RG3TO5	Pseudo-R^2	0.230	0.199	0.145	0.104	0.078	0.050	0.037	0.027	0.000
	t-statistics	4.60*	4.42*	3.99*	3.51*	3.11*	2.58*	2.22*	1.90	0.10
RG5TO10	Pseudo-R^2	0.207	0.166	0.117	0.083	0.061	0.041	0.030	0.022	0.000
	t-statistics	4.47*	4.16*	3.66*	3.18*	2.79*	2.33*	2.00*	1.74	0.01
RG10	Pseudo-R^2	0.191	0.141	0.097	0.070	0.052	0.035	0.025	0.019	0.000
	t-statistics	4.33*	3.91*	3.38*	2.94*	2.57*	2.16*	1.85	1.62	0.16
RRCP90	Pseudo-R^2	0.035	0.041	0.020	0.000	0.000	0.000	0.000	0.000	0.020
	t-statistics	2.12*	2.28*	1.60	0.89	0.80	0.21	-0.11	-0.49	-1.62
RRPRIME	Pseudo-R^2	0.022	0.020	0.006	0.000	0.000	0.000	0.000	0.000	0.018
	t-statistics	1.71	1.64	0.93	0.37	0.32	-0.12	-0.35	-0.75	-1.53
RRTB90	Pseudo-R^2	0.014	0.017	0.011	0.010	0.013	0.013	0.013	0.019	0.039
	t-statistics	1.24	1.33	0.82	0.42	0.51	0.15	-0.07	-0.41	-1.30
RRG1TO3	Pseudo-R^2	0.000	0.000	0.003	0.008	0.005	0.006	0.003	0.001	0.012
	t-statistics	0.10	-0.08	-0.68	-1.04	-0.82	-0.84	-0.62	0.43	-1.27
RRG3TO5	Pseudo-R^2	0.002	0.005	0.014	0.020	0.014	0.011	0.006	0.002	0.012
	t-statistics	-0.57	-0.82	-1.38	-1.64	-1.36	-1.24	-0.92	-0.60	-1.31
RRG5TO10	Pseudo-R^2	0.010	0.017	0.032	0.039	0.028	0.021	0.012	0.006	0.014
	t-statistics	-1.14	-1.52	-2.06*	-2.26*	-1.93	-1.69	-1.30	-0.91	-1.37
RRG10	Pseudo-R^2	0.017	0.031	0.050	0.055	0.040	0.029	0.017	0.009	0.012
	t-statistics	-1.51	-1.99	-2.51*	-2.62*	-2.27*	-1.95	-1.53	-1.08	-1.28
RG10-RCP90	Pseudo-R^2	0.310	0.463	0.404	0.253	0.174	0.083	0.033	0.006	0.002
	t-statistics	-5.08*	-4.90*	-5.07*	-4.91*	-4.38*	-3.23*	-2.11*	-0.89	0.57
RCP90-RTB90	Pseudo-R^2	0.005	0.012	0.014	0.011	0.013	0.016	0.018	0.027	0.037
	t-statistics	0.69	-0.57	-0.56	0.65	0.63	0.62	0.61	-0.11	-0.36
RG10-DY	Pseudo-R^2	0.129	0.116	0.101	0.087	0.069	0.050	0.034	0.023	0.000
	t-statistics	3.76*	3.59*	3.40*	3.20*	2.90*	2.53*	2.12*	1.77	0.02
M1	Pseudo-R^2	0.123	0.009	0.003	0.009	0.006	0.007	0.000	0.014	0.023
	t-statistics	-3.10*	-2.74*	-0.55	-0.91	-0.30	0.77	0.23	1.11	1.43
M2	Pseudo-R^2	0.041	0.108	0.168	0.160	0.182	0.152	0.125	0.122	0.011
	t-statistics	1.88*	2.91*	3.46*	3.37*	3.51*	3.30*	3.06*	3.04*	1.01
M2+	Pseudo-R^2	0.018	0.072	0.127	0.139	0.157	0.133	0.129	0.116	0.024
	t-statistics	1.25	2.41*	3.07*	3.13*	3.22*	3.07*	3.04*	2.93*	1.47
M3	Pseudo-R^2	0.013	0.065	0.079	0.099	0.109	0.051	0.056	0.048	0.030
	t-statistics	1.08	2.37*	2.59*	2.85*	2.97*	2.11*	2.20*	2.04*	1.65

TABLE A.1 (continued)
ESTIMATION RESULTS: ONE-VARIABLE PROBIT MODELS K-QUARTERS AHEAD

		Forecast Horizon								
Variable - X_t	**Statistics**	**k=1**	**k=2**	**k=3**	**k=4**	**k=5**	**k=6**	**k=7**	**k=8**	**k=12**
RM1	Pseudo-R^2	0.271	0.120	0.052	0.074	0.034	0.004	0.008	0.002	0.014
	t-statistics	-4.25*	-3.79*	-2.08*	-2.43*	-1.71	-0.58	-0.85	0.47	1.13
RM2	Pseudo-R^2	0.007	0.008	0.028	0.017	0.040	0.039	0.037	0.092	0.007
	t-statistics	-0.79	0.84	1.58	1.24	1.87	1.84	1.81	2.74*	0.79
RM2+	Pseudo-R^2	0.045	0.000	0.006	0.000	0.018	0.019	0.029	0.079	0.019
	t-statistics	-1.96	-0.09	0.75	0.67	1.26	1.30	1.60	2.51*	1.29
RM3	Pseudo-R^2	0.013	0.005	0.008	0.011	0.023	0.004	0.011	0.028	0.028
	t-statistics	-1.08	0.65	0.84	1.00	1.43	0.58	0.99	1.56	1.55
MCI	Pseudo-R^2	0.414	0.419	0.317	0.210	0.144	0.086	0.052	0.025	0.007
	t-statistics	4.82*	4.80*	4.81*	4.35*	3.83*	3.16*	2.53*	1.80	-0.96
RMCI	Pseudo-R^2	0.000	0.034	0.071	0.050	0.081	0.048	0.080	0.044	0.006
	t-statistics	0.06	2.10*	2.96*	2.53*	3.09*	2.43*	2.47*	2.34*	0.88
PFX	Pseudo-R^2	0.000	0.000	0.012	0.010	0.000	0.000	0.002	0.010	0.000
	t-statistics	0.31	0.49	1.26	1.15	-0.24	-0.07	0.45	1.16	-0.09
RPFX	Pseudo-R^2	0.002	0.001	0.001	0.005	0.000	0.000	0.001	0.018	0.000
	t-statistics	0.47	0.52	0.89	0.89	-0.28	-0.00	0.66	1.55	0.13
TSE	Pseudo-R^2	0.091	0.121	0.036	0.000	0.004	0.032	0.024	0.024	0.013
	t-statistics	-3.36*	-3.76*	-2.18*	-0.21	0.73	2.03*	1.76	1.76	1.33
RTSE	Pseudo-R^2	0.115	0.148	0.057	0.005	0.000	0.017	0.012	0.016	0.009
	t-statistics	-3.75*	-4.11*	-2.70*	-0.83	0.18	1.50	1.27	1.42	1.10
DY	Pseudo-R^2	0.131	0.054	0.007	0.000	0.002	0.006	0.002	0.000	0.002
	t-statistics	3.88*	2.65*	1.00	-0.16	-0.58	-0.84	-0.52	-0.11	0.54
PER	Pseudo-R^2	0.115	0.115	0.102	0.090	0.082	0.078	0.081	0.078	0.031
	t-statistics	-3.17*	-3.17*	-2.95*	-2.75*	-2.60*	-2.56*	-2.67*	-2.67*	-1.67
SCLIS	Pseudo-R^2	0.278	0.130	0.039	0.004	0.002	0.007	0.004	0.000	0.044
	t-statistics	-5.05*	-3.92*	-2.27*	-0.77	0.52	0.97	0.72	0.18	2.26*
SCLINS	Pseudo-R^2	0.294	0.202	0.079	0.020	0.002	0.005	0.006	0.004	0.029
	t-statistics	-5.24*	-4.65*	-3.17*	-1.64	-0.55	0.80	0.87	0.74	1.88
FLI	Pseudo-R^2	0.462	0.319	0.186	0.098	0.052	0.026	0.024	0.017	0.023
	t-statistics	-5.33*	-5.22*	-4.46*	-3.39*	-2.43*	-1.52	-1.33	-0.70	0.39
USRGDP	Pseudo-R^2	0.216	0.091	0.043	0.022	0.004	0.001	0.011	0.015	0.007
	t-statistics	-4.72*	-3.31*	-2.35*	-1.72	-0.69	-0.40	1.22	1.39	0.20
USLI	Pseudo-R^2	0.202	0.124	0.060	0.026	0.009	0.002	0.002	0.000	0.000
	t-statistics	-4.51*	-3.89*	-2.82*	-1.87	-1.10	-0.55	-0.57	-0.20	-0.07
USYC	Pseudo-R^2	0.086	0.190	0.255	0.232	0.230	0.159	0.073	0.024	0.000
	t-statistics	-3.23*	-4.29*	-4.66*	-4.55*	-4.42*	-3.97*	-2.95*	-1.76	0.19
SP500	Pseudo-R^2	0.124	0.097	0.025	0.006	0.000	0.008	0.014	0.009	0.000
	t-statistics	-3.74*	-3.36*	-1.82	-0.85	-0.21	1.05	1.35	1.10	-0.26
RSP500	Pseudo-R^2	0.160	0.126	0.043	0.015	0.004	0.000	0.004	0.002	0.000
	t-statistics	-4.12	-3.75*	-2.35*	-1.44	-0.78	0.43	0.70	0.56	-0.54
RLTCAUS	Pseudo-R^2	0.043	0.019	0.001	0.000	0.003	0.026	0.027	0.007	0.008
	t-statistics	2.34*	1.60	0.44	-0.23	-0.73	-1.81	-1.91	-0.91	-0.98

TABLE A.1 (end)
ESTIMATION RESULTS: ONE-VARIABLE PROBIT MODELS K-QUARTERS AHEAD

		Forecast Horizon								
Variable - X_t	**Statistics**	**k=1**	**k=2**	**k=3**	**k=4**	**k=5**	**k=6**	**k=7**	**k=8**	**k=12**
RSTCAUS	Pseudo-R^2	0.165	0.153	0.063	0.021	0.004	0.004	0.007	0.007	0.006
	t-statistics	4.27*	4.03*	2.83*	1.69	0.70	-0.71	-0.97	-0.95	-0.82
USRYC	Pseudo-R^2	0.102	0.098	0.091	0.078	0.063	0.051	0.033	0.016	0.000
	t-statistics	3.49*	3.41*	3.30*	3.09*	2.82*	2.57*	2.11*	1.45	-0.13
GERYC	Pseudo-R^2	0.127	0.172	0.188	0.187	0.155	0.086	0.024	0.000	0.035
	t-statistics	-3.92*	-4.36*	-4.41*	-4.46*	-4.16*	-3.27*	-1.82	-0.30	1.80
RGDP	Pseudo-R^2	0.150	0.034	0.019	0.012	0.000	0.003	0.005	0.009	0.008
	t-statistics	-3.90*	-2.08*	-1.59	-1.28	0.10	0.66	0.77	1.12	1.05
ΔGBF	Pseudo-R^2	0.047	0.000	0.021	0.000	0.014	0.014	0.008	0.005	0.000
	t-statistics	-2.46*	-0.21	1.65	0.33	1.34	1.36	1.04	0.83	0.29
ΔGRF	Pseudo-R^2	0.004	0.024	0.057	0.016	0.017	0.009	0.002	0.005	0.000
	t-statistics	0.74	1.76	2.66*	1.46	1.51	1.08	0.46	0.79	-0.15
ΔGSF	Pseudo-R^2	0.144	0.035	0.001	0.009	0.001	0.006	0.005	0.001	0.002
	t-statistics	3.94*	2.15*	0.42	1.10	-0.34	-0.93	-0.82	-0.43	-0.57
CC	Pseudo-R^2	0.280	0.129	0.030	0.005	0.000	0.007	0.010	0.027	0.093
	t-statistics	-4.41*	-3.42*	-1.75	-0.76	-0.06	0.86	1.00	1.63	2.80*
ΔCC	Pseudo-R^2	0.108	0.168	0.046	0.019	0.033	0.000	0.015	0.005	0.000
	t-statistics	-3.07*	-3.64*	-2.11*	-1.40	-1.81	-0.26	-1.25	-0.76	-0.31
ΔSTOIR	Pseudo-R^2	0.141	0.088	0.060	0.044	0.007	0.007	0.009	0.011	0.020
	t-statistics	-3.94*	-3.24*	-2.73*	-2.32*	-0.58	0.17	-0.10	-0.00	0.32

TABLE A.2
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS ONE-QUARTER AHEAD
$P(R_{t+1} = 1) = F(\beta_0 + \beta_1 * FLI_t + \beta_2 * X_{i,t-l})$
(1962: Q1 - 1995: Q4)

		Lag *l*								
Variable X_i	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RCP90	Pseudo-R^2	0.516	0.516	0.504	0.500	0.504	0.493	0.486	0.479	0.464
	t-statistics	2.35*	2.26*	2.04*	1.94	2.07*	1.85	1.63	1.37	0.36
RPRIME	Pseudo-R^2	0.499	0.498	0.491	0.492	0.497	0.488	0.483	0.474	0.465
	t-statistics	1.97	1.92	1.73	1.76	1.92	1.70	1.52	1.17	0.52
RTB90	Pseudo-R^2	0.484	0.480	0.480	0.483	0.491	0.483	0.478	0.471	0.463
	t-statistics	1.55	1.39	1.37	1.49	1.74	1.52	1.33	0.99	0.16
RG1TO3	Pseudo-R^2	0.502	0.482	0.486	0.489	0.492	0.485	0.479	0.477	0.463
	t-statistics	2.02*	1.47	1.56	1.66	1.77	1.58	1.37	1.27	0.31
RG3TO5	Pseudo-R^2	0.507	0.485	0.488	0.490	0.475	0.486	0.480	0.478	0.463
	t-statistics	2.12*	1.54	1.64	1.68	1.77	1.62	1.41	1.33	0.26
RG5TO10	Pseudo-R^2	0.509	0.484	0.488	0.491	0.491	0.486	0.480	0.478	0.463
	t-statistics	2.16*	1.53	1.63	1.69	1.73	1.59	1.38	1.31	0.17
RG10	Pseudo-R^2	0.511	0.485	0.487	0.489	0.489	0.484	0.495	0.475	0.463
	t-statistics	2.17*	1.55	1.61	1.67	1.67	1.53	1.30	1.19	0.24
RRCP90	Pseudo-R^2	0.468	0.470	0.471	0.468	0.463	0.463	0.463	0.463	0.465
	t-statistics	-0.81	-0.91	-0.99	-0.79	0.26	0.19	0.12	0.15	-0.50
RRPRIME	Pseudo-R^2	0.470	0.471	0.474	0.469	0.462	0.462	0.462	0.462	0.463
	t-statistics	-0.94	-0.99	-1.12	-0.87	0.09	0.01	-0.01	-0.07	-0.27
RRTB90	Pseudo-R^2	0.478	0.484	0.482	0.474	0.463	0.463	0.463	0.463	0.467
	t-statistics	-1.29	-1.50	-1.43	-1.13	-0.10	-0.12	-0.17	-0.21	-0.72
RRG1TO3	Pseudo-R^2	0.478	0.474	0.485	0.480	0.465	0.465	0.465	0.463	0.465
	t-statistics	-1 10	-1.73	-1.52	-1.37	-0.57	-0.57	-0.59	0.15	-0.57
RRG3TO5	Pseudo-R^2	0.474	0.493	0.486	0.484	0.468	0.467	0.467	0.463	0.464
	t-statistics	-1.12	-1.76	-1.57	-1.51	-0.79	-0.75	-0.73	-0.23	-0.66
RRG5TO10	Pseudo-R^2	0.476	0.496	0.490	0.488	0.471	0.470	0.469	0.464	0.467
	t-statistics	-1.20	-1.83	-1.67	-1.63	-1.01	-0.92	-0.88	-0.33	-0.76
RRG10	Pseudo-R^2	0.477	0.498	0.492	0.490	0.474	0.471	0.470	0.464	0.466
	t-statistics	-1.23	-1.85	-1.71	-1.69	-1.12	-1.00	-0.95	-0.44	-0.68
RG10-RCP90	Pseudo-R^2	0.473	0.529	0.496	0.486	0.503	0.486	0.480	0.470	0.464
	t-statistics	-1.12	-2.42*	-1.82	-1.59	-2.10*	-1.63	-1.41	-0.95	-0.38
RCP90-RTB90	Pseudo-R^2	0.470	0.464	0.463	0.513	0.486	0.476	0.471	0.468	0.468
	t-statistics	0.93	-0.31	-0.00	2.31*	1.33	0.92	0.66	-0.18	-0.17
RG10-DY	Pseudo-R^2	0.495	0.477	0.490	0.497	0.499	0.496	0.487	0.479	0.464
	t-statistics	1.82	1.27	1.66	1.84	1.92	1.88	1.62	1.36	0.36
M1	Pseudo-R^2	0.504	0.520	0.525	0.509	0.509	0.527	0.505	0.511	0.517
	t-statistics	-0.31	-1.22	-1.37	-0.73	-0.76	1.42	-0.43	0.83	1.09
M2	Pseudo-R^2	0.504	0.511	0.519	0.508	0.557	0.602	0.570	0.604	0.519
	t-statistics	0.37	0.84	1.17	0.69	1.89	2.38*	2.17*	2.53*	1.16
M2+	Pseudo-R^2	0.503	0.511	0.514	0.507	0.534	0.574	0.577	0.578	0.521
	t-statistics	0.13	0.84	0.98	0.62	1.45	2.00*	2.15*	2.21*	1.26
M3	Pseudo-R^2	0.503	0.513	0.504	0.503	0.524	0.506	0.525	0.541	0.506
	t-statistics	0.06	0.95	0.32	0.27	1.33	0.53	1.36	1.74	0.52

TABLE A.2 (continued)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS ONE-QUARTER AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RM1	Pseudo-R^2	0.521	0.554	0.504	0.552	0.541	0.505	0.526	0.504	0.506
	t-statistics	-1.24	-2.00*	0.32	-1.86	-1.71	0.49	-1.36	0.39	0.55
RM2	Pseudo-R^2	0.512	0.505	0.506	0.506	0.505	0.527	0.506	0.593	0.505
	t-statistics	-0.90	-0.51	-0.53	-1.54	0.34	1.42	0.57	2.44*	0.47
RM2+	Pseudo-R^2	0.523	0.507	0.511	0.541	0.504	0.511	0.505	0.571	0.505
	t-statistics	-1.30	-0.62	-0.85	-1.75	-0.40	0.84	0.45	2.16*	0.49
RM3	Pseudo-R^2	0.512	0.503	0.512	0.528	0.502	0.507	0.503	0.528	0.503
	t-statistics	-0.90	0.04	-0.89	-1.43	-0.01	-0.59	-0.17	1.47	-0.07
MCI	Pseudo-R^2	0.615	0.609	0.582	0.573	0.583	0.580	0.579	0.556	0.470
	t-statistics	3.09*	3.06*	2.97*	2.87*	2.90*	3.04*	3.00*	2.69*	0.91
RMCI	Pseudo-R^2	0.477	0.478	0.480	0.488	0.545	0.545	0.533	0.524	0.470
	t-statistics	1.22	1.28	1.31	1.55	2.33*	2.39*	2.33*	2.28*	0.93
PFX	Pseudo-R^2	0.462	0.464	0.463	0.467	0.490	0.468	0.464	0.468	0.463
	t-statistics	0.08	-0.38	-0.15	0.69	-1.69	-0.78	0.39	0.76	-0.22
RPFX	Pseudo-R^2	0.463	0.471	0.477	0.464	0.501	0.467	0.462	0.470	0.463
	t-statistics	-0.18	-0.95	-1.25	-0.43	-1.93	-0.69	-0.03	0.93	0.19
TSE	Pseudo-R^2	0.480	0.579	0.495	0.478	0.472	0.464	0.470	0.464	0.473
	t-statistics	-1.43	-3.14*	-1.90	-1.34	-1.04	0.44	0.91	0.45	1.09
RTSE	Pseudo-R^2	0.485	0.592	0.508	0.489	0.478	0.463	0.465	0.463	0.470
	t-statistics	-1.61	-3.21*	-2.21*	-1.72	1.32	0.16	0.58	0.32	0.92
DY	Pseudo-R^2	0.501	0.486	0.464	0.463	0.467	0.475	0.472	0.465	0.464
	t-statistics	1.98*	1.59	0.48	-0.26	-0.72	-1.17	-1.02	-0.51	-0.39
PER	Pseudo-R^2	0.469	0.473	0.471	0.470	0.469	0.470	0.471	0.475	0.470
	t-statistics	-0.82	-1.09	-0.93	-0.83	-0.65	-0.54	-0.60	-0.80	-0.63
SCLIS	Pseudo-R^2	0.494	0.512	0.508	0.483	0.463	0.467	0.463	0.468	0.487
	t-statistics	-1.84	-2.26*	-2.17*	-1.53	0.15	0.70	0.21	-0.83	1.59
SCLINS	Pseudo-R^2	0.463	0.511	0.490	0.498	0.479	0.471	0.463	0.464	0.492
	t-statistics	-0.20	-2.25*	-1.74	-1.96	-1.38	0.96	0.29	0.41	1.70
USRGDP	Pseudo-R^2	0.484	0.484	0.503	0.514	0.467	0.463	0.464	0.476	0.472
	t-statistics	-1.58	-1.51	-2.04*	-2.27*	-0.74	-0.27	0.49	1.23	-0.99
USLI	Pseudo-R^2	0.5xx	0.563	0.558	0.566	0.550	0.548	0.548	0.550	0.550
	t-statistics	0.39	-1.28	-1.04	-1.41	-1.47	-0.15	-0.06	0.50	-0.51
USYC	Pseudo-R^2	0.463	0.468	0.487	0.489	0.542	0.532	0.495	0.489	0.480
	t-statistics	-0.17	-0.78	-1.61	-1.68	-2.60*	-2.52*	-2.08*	-1.65	-1.36
DJI	Pseudo-R^2	0.484	0.492	0.466	0.478	0.471	0.462	0.482	0.466	0.463
	t-statistics	-1.56	-1.80	-0.66	-1.35	-0.98	0.06	1.45	0.67	-0.17
SP500	Pseudo-R^2	0.507	0.513	0.477	0.483	0.472	0.466	0.486	0.473	0.464
	t-statistics	-2.16*	-2.24*	-1.28	-1.52	-1.03	0.61	1.58	1.07	0.36
RSP500	Pseudo-R^2	0.513	0.516	0.479	0.486	0.476	0.463	0.477	0.469	0.462
	t-statistics	-2.25*	-2.27*	-1.40	-1.65	-1.25	0.27	1.28	0.85	0.03
RLTCAUS	Pseudo-R^2	0.469	0.464	0.463	0.463	0.463	0.482	0.490	0.466	0.531
	t-statistics	0.88	0.42	0.23	0.24	0.32	-1.43	-1.70	-0.65	-2.50*

TABLE A.2 (end)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS ONE-QUARTER AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RSTCAUS	Pseudo-R^2	0.472	0.487	0.464	0.464	0.463	0.470	0.470	0.470	0.502
	t-statistics	1.06	1.62	0.38	0.42	0.29	-0.90	-0.82	-0.81	-1.83
USRYC	Pseudo-R^2	0.498	0.482	0.498	0.506	0.507	0.513	0.499	0.480	0.464
	t-statistics	1.93	1.46	1.88	2.04*	2.09*	2.24*	1.95	1.41	0.47
GERYC	Pseudo-R^2	0.493	0.573	0.586	0.629	0.623	0.581	0.513	0.479	0.471
	t-statistics	-1.87	-3.06*	-3.18*	-3.34*	-3.21*	-3.21*	-2.35*	-1.37	-0.74
RGDP	Pseudo-R^2	0.470	0.462	0.479	0.505	0.463	0.467	0.466	0.475	0.474
	t-statistics	-0.93	0.01	-1.35	-2.12	-0.11	0.73	0.61	1.17	1.15
ΔGBF	Pseudo-R^2	0.478	0.462	0.471	0.526	0.475	0.474	0.464	0.470	0.462
	t-statistics	-1.29	-0.08	0.96	-2.42*	1.16	1.13	0.42	0.91	0.06
ΔGRF	Pseudo-R^2	0.471	0.465	0.481	0.471	0.492	0.493	0.464	0.503	0.467
	t-statistics	0.99	0.53	1.42	-0.95	1.76	1.80	0.36	2.02*	0.75
ΔGSF	Pseudo-R^2	0.541	0.471	0.462	0.536	0.463	0.462	0.463	0.465	0.464
	t-statistics	2.73*	0.98	-0.06	2.62*	0.25	-0.01	0.15	0.59	0.47
CC	Pseudo-R^2	0.570	0.558	0.533	0.552	0.547	0.519	0.513	0.512	0.514
	t-statistics	-2.25*	-2.05*	-1.43	-1.92	-1.82	-0.88	-0.73	0.37	0.55
ΔCC	Pseudo-R^2	0.511	0.539	0.519	0.513	0.569	0.511	0.544	0.512	0.520
	t-statistics	-0.17	-1.60	0.87	-0.41	-2.24*	-0.24	-1.69	0.28	-0.94
ΔSTOIR	Pseudo-R^2	0.471	0.465	0.463	0.502	0.465	0.471	0.481	0.468	0.468
	t-statistics	0.95	-0.54	-0.29	-2.03*	-0.50	0.96	-1.24	0.27	-0.33

TABLE A.3
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS TWO-QUARTERS AHEAD
$P(R_{t+2} = 1) = F(\beta_0 + \beta_1 * (RG10_t - RCP90_t) + \beta_2 * X_{i,t-l})$
(1962: Q1 - 1995: Q4)

		Lag *l*								
Variable X_i	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RCP90	Pseudo-R^2	0.507	0.495	0.499	0.498	0.482	0.475	0.468	0.468	
	t-statistics	1.76	1.84	1.94	1.92	1.49	1.19	0.75	0.81	
RPRIME	Pseudo-R^2	0.482	0.486	0.490	0.489	0.478	0.472	0.466	0.466	
	t-statistics	1.42	1.58	1.72	1.70	1.31	1.01	0.63	0.64	
RTB90	Pseudo-R^2	0.473	0.478	0.486	0.488	0.478	0.472	0.467	0.465	
	t-statistics	1.05	1.29	1.60	1.66	1.32	1.06	0.66	0.54	
RG1TO3	Pseudo-R^2	0.490	0.484	0.490	0.485	0.473	0.472	0.470	0.464	
	t-statistics	1.70	1.50	1.69	1.57	1.09	1.06	0.92	0.39	
RG3TO5	Pseudo-R^2	0.494	0.486	0.492	0.486	0.475	0.474	0.473	0.463	
	t-statistics	1.81	1.58	1.75	1.59	1.18	1.15	1.07	0.25	
RG5TO10	Pseudo-R^2	0.496	0.487	0.491	0.485	0.475	0.474	0.473	0.463	
	t-statistics	1.84	1.61	1.74	1.54	1.17	1.16	1.11	0.11	
RG10	Pseudo-R^2	0.493	0.484	0.489	0.481	0.472	0.472	0.471	0.463	
	t-statistics	1.76	1.52	1.65	1.42	1.05	1.01	0.97	0.04	
RRCP90	Pseudo-R^2	0.467	0.464	0.463	0.464	0.463	0.463	0.465	0.463	
	t-statistics	-0.65	-0.40	0.01	0.36	-0.00	-0.24	-0.48	0.06	
RRPRIME	Pseudo-R^2	0.467	0.465	0.463	0.463	0.463	0.463	0.464	0.463	
	t-statistics	-0.69	-0.51	-0.18	0.08	-0.22	-0.44	-0.61	-0.21	
RRTB90	Pseudo-R^2	0.472	0.469	0.464	0.463	0.463	0.463	0.465	0.463	
	t-statistics	-1.00	-0.82	-0.31	0.10	-0.11	-0.29	-0.49	-0.24	
RRG1TO3	Pseudo-R^2	0.465	0.470	0.466	0.465	0.469	0.467	0.465	0.465	
	t-statistics	-0.50	-0.87	-0.60	-0.50	-0.87	-0.68	-0.45	-0.56	
RRG3TO5	Pseudo-R^2	0.465	0.470	0.467	0.467	0.471	0.467	0.464	0.468	
	t-statistics	-0.47	-0.93	-0.72	-0.66	-0.93	-0.71	-0.41	-0.74	
RRG5TO10	Pseudo-R^2	0.465	0.472	0.470	0.470	0.473	0.468	0.464	0.470	
	t-statistics	-0.52	-1.01	-0.90	-0.89	-1.06	-0.78	-0.43	-0.90	
RRG10	Pseudo-R^2	0.467	0.475	0.473	0.474	0.477	0.471	0.466	0.471	
	t-statistics	-0.65	-1.17	-1.07	-1.11	-1.22	-0.96	-0.57	-0.95	
RCP90-RTB90	Pseudo-R^2	0.464	0.466	0.468	0.482	0.469	0.474	0.470	0.468	
	t-statistics	-0.26	-0.35	0.77	1.44	0.68	1.01	-0.29	-0.30	
RG10-DY	Pseudo-R^2	0.484	0.486	0.499	0.490	0.480	0.477	0.473	0.463	
	t-statistics	1.52	1.58	1.91	1.70	1.41	1.28	1.09	-0.14	
M1	Pseudo-R^2	0.547	0.530	0.538	0.535	0.532	0.537	0.560	0.530	
	t-statistics	-1.21	-0.19	-0.82	-0.68	0.45	0.79	1.47	0.05	
M2	Pseudo-R^2	0.530	0.530	0.533	0.543	0.543	0.583	0.615	0.533	
	t-statistics	-0.16	0.17	0.48	1.05	1.07	1.92	2.40*	0.50	
M2+	Pseudo-R^2	0.532	0.530	0.531	0.537	0.539	0.587	0.593	0.539	
	t-statistics	-0.48	-0.06	0.25	0.74	0.87	1.91	2.07*	0.88	
M3	Pseudo-R^2	0.533	0.530	0.532	0.536	0.530	0.536	0.533	0.530	
	t-statistics	-0.55	-0.18	0.40	0.72	0.03	0.69	0.56	0.15	

TABLE A.3 (continued)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS TWO-QUARTERS AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RM1	Pseudo-R^2	0.565	0.538	0.573	0.562	0.533	0.530	0.537	0.532	
	t-statistics	-1.66	-0.84	-1.78	-1.59	-0.56	-0.17	0.78	-0.40	
RM2	Pseudo-R^2	0.541	0.543	0.556	0.538	0.541	0.530	0.559	0.531	
	t-statistics	-0.96	-1.05	-1.44	-0.85	-0.96	0.24	1.55	-0.26	
RM2+	Pseudo-R^2	0.550	0.592	0.614	0.591	0.596	0.571	0.582	0.571	
	t-statistics	-1.28	-1.33	-1.83	-1.30	-1.40	0.00	1.01	0.04	
RM3	Pseudo-R^2	0.544	0.541	0.539	0.534	0.561	0.536	0.532	0.532	
	t-statistics	-1.09	-0.99	-0.87	-0.62	-1.52	-0.75	-0.45	-0.45	
MCI	Pseudo-R^2	0.541	0.540	0.543	0.550	0.530	0.529	0.513	0.482	
	t-statistics	2.56*	2.56*	2.68*	2.74*	2.55*	2.47*	2.20*	1.46	
RMCI	Pseudo-R^2	0.473	0.481	0.501	0.528	0.516	0.511	0.504	0.483	
	t-statistics	1.03	1.33	1.78	2.23*	2.15*	2.12*	1.97	1.45	
PFX	Pseudo-R^2	0.464	0.469	0.464	0.488	0.485	0.475	0.463	0.466	
	t-statistics	-0.31	0.83	-0.35	-1.61	-1.56	-1.17	0.01	-065	
RPFX	Pseudo-R^2	0.466	0.463	0.472	0.499	0.494	0.479	0.466	0.463	
	t-statistics	-0.61	-0.00	-1.01	-1.90	-1.82	-1.35	-0.26	-0.17	
TSE	Pseudo-R^2	0.578	0.533	0.471	0.469	0.467	0.467	0.474	0.467	
	t-statistics	-3.06*	-2.50*	-0.96	-0.86	0.71	0.67	1.13	0.73	
RTSE	Pseudo-R^2	0.579	0.543	0.477	0.473	0.464	0.464	0.471	0.466	
	t-statistics	-3.10*	-2.62*	-1.25	-1.08	0.41	0.40	0.96	0.59	
DY	Pseudo-R^2	0.492	0.466	0.465	0.469	0.475	0.468	0.464	0.465	
	t-statistics	1.75	0.61	-0.45	-0.80	-1.15	-0.78	-0.30	0.52	
PER	Pseudo-R^2	0.465	0.463	0.463	0.463	0.463	0.463	0.466	0.472	
	t-statistics	-0.53	-0.13	0.22	0.27	0.01	-0.24	-0.62	-1.00	
SCLIS	Pseudo-R^2	0.543	0.503	0.465	0.485	0.520	0.467	0.472	0.463	
	t-statistics	-2.66*	-2.04*	-0.50	1.51	2.32*	0.71	-1.03	-0.20	
SCLINS	Pseudo-R^2	0.514	0.533	0.483	0.464	0.487	0.499	0.463	0.466	
	t-statistics	-2.26*	-2.56*	-1.51	-0.35	1.60	1.95	0.28	-0.63	
FLI	Pseudo-R^2	0.482	0.492	0.483	0.466	0.465	0.473	0.469	0.489	
	t-statistics	-1.46	-1.76	-1.49	-0.63	0.50	1.00	0.77	-1.50	
USRGDP	Pseudo-R^2	0.513	0.501	0.481	0.466	0.463	0.495	0.463	0.481	
	t-statistics	-2.25*	-1.95	-1.43	-0.60	0.14	1.80	0.16	-1.40	
USLI	Pseudo-R^2	0.472	0.500	0.477	0.463	0.466	0.513	0.477	0.506	
	t-statistics	-1.00	-1.99*	-1.26	-0.14	0.63	1.63	1.23	-2.14*	
USYC	Pseudo-R^2	0.483	0.467	0.506	0.566	0.553	0.504	0.475	0.503	
	t-statistics	0.26	-0.69	-2.05*	-2.80*	-2.76*	-1.98*	-1.13	-1.94	
DJI	Pseudo-R^2	0.543	0.493	0.486	0.480	0.467	0.478	0.480	0.471	
	t-statistics	-2.66*	-1.80	-1.58	-1.39	0.70	1.24	1.36	-0.93	
SP500	Pseudo-R^2	0.561	0.502	0.502	0.485	0.469	0.497	0.496	0.463	
	t-statistics	-2.75*	-2.03*	-1.97	-1.60	0.81	1.80	1.84	-0.16	
RSP500	Pseudo-R^2	0.555	0.503	0.506	0.488	0.466	0.487	0.491	0.464	
	t-statistics	-2.68*	-2.03*	-2.05	-1.66	0.55	1.56	1.70	-0.43	

TABLE A.3 (end)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS TWO-QUARTERS AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RLTCAUS	Pseudo-R^2	0.464	0.466	0.470	0.464	0.488	0.487	0.464	0.549	
	t-statistics	0.39	0.59	0.93	0.34	-1.60	-1.61	0.32	2.72*	
RSTCAUS	Pseudo-R^2	0.464	0.471	0.465	0.463	0.473	0.481	0.473	0.470	
	t-statistics	0.33	0.94	0.55	0.28	-1.02	-1.34	-1.05	-0.91	
USRYC	Pseudo-R^2	0.488	0.490	0.502	0.497	0.494	0.487	0.471	0.463	
	t-statistics	1.64	1.68	2.00*	1.89	1.85	1.66	0.96	-0.01	
GERYC	Pseudo-R^2	0.496	0.519	0.543	0.565	0.517	0.497	0.484	0.473	
	t-statistics	-1.89	-2.33*	-2.74*	-2.97*	-2.38*	-1.98*	-1.56	-1.09	
RGDP	Pseudo-R^2	0.469	0.477	0.488	0.465	0.488	0.473	0.464	0.463	
	t-statistics	-0.85	-1.24	-1.61	0.51	1.61	1.08	0.29	0.07	
ΔGBF	Pseudo-R^2	0.467	0.466	0.472	0.465	0.512	0.477	0.463	0.463	
	t-statistics	-0.66	0.61	-1.05	0.49	2.13*	1.22	0.04	0.12	
ΔGRF	Pseudo-R^2	0.463	0.473	0.470	0.480	0.515	0.469	0.469	0.470	
	t-statistics	0.08	1.09	0.89	1.38	2.27*	0.82	0.82	0.89	
ΔGSF	Pseudo-R^2	0.474	0.464	0.529	0.467	0.526	0.468	0.469	0.466	
	t-statistics	1.15	0.29	2.42*	0.72	-1.11	-0.79	0.83	0.61	
CC	Pseudo-R^2	0.545	0.531	0.536	0.545	0.517	0.522	0.522	0.505	
	t-statistics	-1.90	-1.55	-1.71	-1.87	-1.06	-1.22	-1.21	-0.15	
ΔCC	Pseudo-R^2	0.515	0.505	0.505	0.548	0.505	0.505	0.506	0.528	
	t-statistics	-0.92	0.05	-0.06	-1.98	0.10	-0.01	0.34	-1.46	
ΔSTOIR	Pseudo-R^2	0.468	0.496	0.487	0.466	0.486	0.497	0.465	0.480	
	t-statistics	-0.76	-1.86	-1.61	0.59	1.55	1.88	0.32	-1.28	

TABLE A.4
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS THREE-QUARTERS AHEAD
$P(R_{t+3} = 1) = F(\beta_0 + \beta_1 * (RG10_t - RCP90_t) + \beta_2 * X_{i,t-l})$
(1962: Q1 - 1995: Q4)

		Lag *l*								
Variable X_i	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RCP90	Pseudo-R^2	0.411	0.409	0.415	0.408	0.406	0.404	0.405		
	t-statistics	0.93	0.80	1.13	0.73	0.51	0.15	0.27		
RPRIME	Pseudo-R^2	0.408	0.409	0.412	0.407	0.405	0.404	0.405		
	t-statistics	0.65	0.74	0.99	0.65	0.42	-0.06	0.27		
RTB90	Pseudo-R^2	0.406	0.405	0.412	0.408	0.406	0.404	0.404		
	t-statistics	0.44	0.52	0.97	0.67	0.50	0.11	0.14		
RG1TO3	Pseudo-R^2	0.411	0.408	0.413	0.408	0.406	0.406	0.404		
	t-statistics	0.91	0.71	1.05	0.69	0.51	0.51	0.01		
RG3TO5	Pseudo-R^2	0.413	0.410	0.415	0.409	0.407	0.408	0.404		
	t-statistics	1.02	0.84	1.14	0.78	0.64	0.71	-0.12		
RG5TO10	Pseudo-R^2	0.413	0.411	0.415	0.410	0.408	0.409	0.404		
	t-statistics	1.01	0.89	1.13	0.82	0.68	0.78	-0.17		
RG10	Pseudo-R^2	0.411	0.411	0.414	0.409	0.407	0.408	0.404		
	t-statistics	0.93	0.90	1.09	0.77	0.59	0.69	-0.17		
RRCP90	Pseudo-R^2	0.421	0.414	0.404	0.405	0.405	0.406	0.404		
	t-statistics	-1.39	-1.10	-0.03	-0.27	-0.31	-0.53	-0.07		
RRPRIME	Pseudo-R^2	0.421	0.413	0.404	0.405	0.405	0.405	0.405		
	t-statistics	-1.39	-1.00	-0.16	-0.35	-0.41	-0.76	-0.08		
RRTB90	Pseudo-R^2	0.423	0.416	0.404	0.405	0.405	0.406	0.404		
	t-statistics	-1.44	-1.17	-0.15	-0.26	-0.26	-0.52	-0.21		
RRG1TO3	Pseudo-R^2	0.416	0.417	0.405	0.406	0.406	0.405	0.406		
	t-statistics	-1.17	-1.21	-0.30	-0.48	-0.46	-0.22	-0.40		
RRG3TO5	Pseudo-R^2	0.415	0.416	0.405	0.406	0.406	0.404	0.407		
	t-statistics	-1.15	-1.18	-0.32	-0.47	-0.39	-0.08	-0.55		
RRG5TO10	Pseudo-R^2	0.417	0.417	0.406	0.407	0.406	0.404	0.407		
	t-statistics	-1.24	-1.21	-0.43	-0.52	-0.41	-0.06	-0.59		
RRG10	Pseudo-R^2	0.421	0.418	0.407	0.408	0.407	0.404	0.407		
	t-statistics	-1.39	-1.26	-0.52	-0.60	-0.52	-0.15	-0.58		
RCP90-RTB90	Pseudo-R^2	0.406	0.422	0.409	0.421	0.411	0.418	0.407		
	t-statistics	-0.27	1.49	0.78	1.39	0.75	-0.37	-0.12		
RG10-DY	Pseudo-R^2	0.419	0.419	0.423	0.415	0.410	0.409	0.405		
	t-statistics	1.30	1.32	1.48	1.12	0.82	0.79	-0.31		
M1	Pseudo-R^2	0.527	0.490	0.486	0.502	0.487	0.534	0.486		
	t-statistics	1.84	-0.57	0.21	1.13	-0.24	1.88	0.10		
M2	Pseudo-R^2	0.498	0.486	0.496	0.490	0.491	0.538	0.488		
	t-statistics	0.99	0.06	0.93	0.61	0.67	1.90	0.41		
M2+	Pseudo-R^2	0.495	0.487	0.491	0.488	0.496	0.524	0.491		
	t-statistics	0.89	0.26	0.67	0.40	0.92	1.65	0.66		
M3	Pseudo-R^2	0.487	0.487	0.492	0.493	0.487	0.488	0.486		
	t-statistics	-0.11	0.35	0.69	-0.78	0.25	0.44	-0.05		

TABLE A.4 (continued)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS THREE-QUARTERS AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RM1	Pseudo-R^2	0.505	0.506	0.488	0.488	0.495	0.532	0.486		
	t-statistics	1.27	-1.27	-0.44	0.47	-0.85	-1.82	-0.17		
RM2	Pseudo-R^2	0.486	0.506	0.487	0.489	0.492	0.536	0.486		
	t-statistics	0.08	-1.28	-0.28	-0.53	-0.68	-1.98	-0.01		
RM2+	Pseudo-R^2	0.486	0.502	0.491	0.414	0.490	0.524	0.486		
	t-statistics	-0.14	-1.17	-0.69	-0.82	-0.58	1.74	0.20		
RM3	Pseudo-R^2	0.493	0.489	0.486	0.520	0.494	0.488	0.488		
	t-statistics	-0.76	-0.55	-0.11	-1.62	-0.80	0.42	-0.46		
MCI	Pseudo-R^2	0.435	0.423	0.432	0.427	0.425	0.418	0.409		
	t-statistics	1.80	1.44	1.73	1.61	1.55	1.29	0.73		
RMCI	Pseudo-R^2	0.404	0.415	0.406	0.406	0.414	0.411	0.404		
	t-statistics	0.12	-1.12	0.54	0.46	1.07	0.93	-0.24		
PFX	Pseudo-R^2	0.409	0.409	0.455	0.415	0.406	0.404	0.416		
	t-statistics	0.78	0.76	-2.21*	-1.14	-0.47	0.15	-1.17		
RPFX	Pseudo-R^2	0.404	0.404	0.458	0.418	0.407	0.405	0.411		
	t-statistics	-0.12	0.07	-2.33*	-1.26	-0.60	0.31	-0.90		
TSE	Pseudo-R^2	0.415	0.404	0.408	0.417	0.405	0.405	0.405		
	t-statistics	-1.12	0.01	0.67	1.20	0.47	0.47	0.49		
RTSE	Pseudo-R^2	0.419	0.404	0.404	0.413	0.404	0.405	0.405		
	t-statistics	-1.32	-0.20	0.49	1.01	0.24	0.41	0.39		
DY	Pseudo-R^2	0.409	0.419	0.417	0.417	0.409	0.404	0.404		
	t-statistics	-0.76	-1.25	-1.19	-1.19	-0.73	-0.26	0.40		
PER	Pseudo-R^2	0.404	0.404	0.404	0.404	0.404	0.404	0.407		
	t-statistics	-0.14	0.07	0.24	0.14	-0.17	-0.33	-0.60		
SCLIS	Pseudo-R^2	0.404	0.404	0.422	0.440	0.419	0.405	0.405		
	t-statistics	-0.27	0.11	1.37	1.91	1.26	-0.40	0.46		
SCLINS	Pseudo-R^2	0.404	0.404	0.404	0.434	0.421	0.419	0.411		
	t-statistics	-0.11	-0.34	0.05	1.69	1.36	1.28	0.89		
FLI	Pseudo-R^2	0.407	0.404	0.404	0.408	0.406	0.431	0.408		
	t-statistics	0.62	-0.00	-0.10	0.71	0.48	1.68	-0.46		
USRGDP	Pseudo-R^2	0.413	0.411	0.404	0.404	0.447	0.445	0.408		
	t-statistics	-1.02	-0.91	-0.34	-0.24	2.13*	2.04*	-0.73		
USLI	Pseudo-R^2	0.404	0.405	0.404	0.406	0.404	0.434	0.408		
	t-statistics	0.33	-0.85	-0.12	0.66	0.30	1.82	-0.74		
USYC	Pseudo-R^2	0.417	0.409	0.449	0.439	0.415	0.404	0.414		
	t-statistics	-1.20	-0.75	-2.08*	-1.88	-1.10	-0.20	-1.03		
DJI	Pseudo-R^2	0.406	0.406	0.407	0.404	0.411	0.407	0.404		
	t-statistics	-0.53	-0.59	-0.61	0.33	0.87	0.65	-0.29		
SP500	Pseudo-R^2	0.409	0.408	0.407	0.407	0.420	0.419	0.406		
	t-statistics	-0.79	-0.66	-0.61	0.58	1.34	1.27	0.44		
RSP500	Pseudo-R^2	0.410	0.409	0.408	0.405	0.414	0.416	0.405		
	t-statistics	-0.83	-0.76	-0.71	0.39	1.07	1.15	0.27		
RLTCAUS	Pseudo-R^2	0.412	0.404	0.404	0.418	0.429	0.404	0.443		
	t-statistics	-0.97	-0.21	0.23	-1.22	-1.63	0.28	-1..97		

TABLE A.4 (end)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS THREE-QUARTERS AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RSTCAUS	Pseudo-R^2	0.417	0.406	0.407	0.423	0.419	0.415	0.408		
	t-statistics	-1.22	-0.46	-0.60	-1.40	-1.25	-1.07	-0.69		
USRYC	Pseudo-R^2	0.425	0.421	0.426	0.423	0.416	0.409	0.404		
	t-statistics	1.52	1.38	1.57	1.49	1.19	0.74	-0.13		
GERYC	Pseudo-R^2	0.453	0.469	0.465	0.434	0.407	0.404	0.412		
	t-statistics	-2.27*	-2.58*	-2.51*	-1.85	-0.60	0.03	-1.02		
RGDP	Pseudo-R^2	0.404	0.411	0.404	0.420	0.423	0.423	0.404		
	t-statistics	-0.19	-0.92	0.47	1.31	1.43	1.46	0.24		
ΔGBF	Pseudo-R^2	0.424	0.412	0.407	0.406	0.422	0.410	0.404		
	t-statistics	1.49	-0.95	0.55	0.52	1.39	0.85	0.07		
ΔGRF	Pseudo-R^2	0.420	0.405	0.413	0.408	0.411	0.419	0.407		
	t-statistics	1.33	-0.30	1.02	0.69	0.91	1.30	0.56		
ΔGSF	Pseudo-R^2	0.414	0.419	0.405	0.404	0.410	0.404	0.405		
	t-statistics	1.08	1.32	0.26	-0.25	-0.86	-0.01	0.36		
CC	Pseudo-R^2	0.447	0.444	0.448	0.445	0.448	0.445	0.445		
	t-statistics	0.77	-0.13	-0.59	-0.28	-0.57	0.21	0.22		
ΔCC	Pseudo-R^2	0.475	0.453	0.448	0.456	0.463	0.446	0.447		
	t-statistics	1.69	0.96	-0.72	0.49	-1.33	0.53	-0.58		
ΔSTOIR	Pseudo-R^2	0.404	0.415	0.410	0.427	0.412	0.433	0.408		
	t-statistics	0.11	-1.11	0.83	1.58	0.94	1.75	-0.40		

TABLE A.5
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS FOUR-QUARTERS AHEAD
$P(R_{t+4} = 1) = F(\beta_0 + \beta_1 * (RG10_t - RCP90_t) + \beta_2 * X_{i,t-l})$
(1962: Q1 - 1995: Q4)

		Lag *l*								
Variable X_i	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RCP90	Pseudo-R^2	0.261	0.259	0.256	0.254	0.253	0.253			
	t-statistics	1.02	0.89	0.63	0.43	0.08	-0.22			
RPRIME	Pseudo-R^2	0.259	0.259	0.256	0.254	0.253	0.253			
	t-statistics	0.85	0.85	0.61	0.40	-0.07	-0.13			
RTB90	Pseudo-R^2	0.257	0.257	0.256	0.254	0.253	0.253			
	t-statistics	0.74	0.75	0.63	0.47	0.64	0.19			
RG1TO3	Pseudo-R^2	0.261	0.258	0.258	0.257	0.255	0.253			
	t-statistics	1.02	0.78	0.78	0.69	0.49	-0.16			
RG3TO5	Pseudo-R^2	0.263	0.259	0.259	0.257	0.256	0.253			
	t-statistics	1.11	0.88	0.88	0.77	0.66	-0.18			
RG5TO10	Pseudo-R^2	0.261	0.259	0.259	0.257	0.256	0.253			
	t-statistics	1.04	0.86	0.91	0.78	0.68	-0.16			
RG10	Pseudo-R^2	0.261	0.259	0.259	0.257	0.256	0.254			
	t-statistics	1.02	0.88	0.91	0.73	0.63	0.40			
RRCP90	Pseudo-R^2	0.276	0.257	0.254	0.254	0.254	0.257			
	t-statistics	-1.68	-0.77	-0.49	-0.44	-0.58	-0.79			
RRPRIME	Pseudo-R^2	0.273	0.257	0.254	0.254	0.257	0.256			
	t-statistics	-1.55	-0.68	-0.46	-0.44	-0.74	-0.63			
RRTB90	Pseudo-R^2	0.272	0.257	0.254	0.254	0.255	0.256			
	t-statistics	-1.51	-0.74	-0.37	-0.32	-0.49	-0.66			
RRG1TO3	Pseudo-R^2	0.270	0.260	0.254	0.253	0.253	0.256			
	t-statistics	-1.43	-0.93	-0.40	-0.23	-0.16	-0.64			
RRG3TO5	Pseudo-R^2	0.270	0.260	0.254	0.253	0.253	0.256			
	t-statistics	-1.44	-0.93	-0.38	-0.22	-0.04	-0.66			
RRG5TO10	Pseudo-R^2	0.273	0.261	0.254	0.253	0.253	0.256			
	t-statistics	-1.60	-1.02	-0.42	-0.27	-0.06	-0.63			
RRG10	Pseudo-R^2	0.276	0.262	0.254	0.253	0.252	0.254			
	t-statistics	-1.68	-1.04	-0.44	-0.35	-0.12	-0.56			
RCP90-RTB90	Pseudo-R^2	0.276	0.264	0.254	0.253	0.253	0.254			
	t-statistics	-1.68	-1.04	-0.44	-0.35	-0.12	-0.56			
RG10-DY	Pseudo-R^2	0.277	0.269	0.268	0.260	0.257	0.253			
	t-statistics	1.69	1.41	1.36	0.96	0.72	-0.20			
M1	Pseudo-R^2	0.334	0.320	0.349	0.318	0.334	0.333			
	t-statistics	1.21	0.47	1.62	0.26	1.17	1.15			
M2	Pseudo-R^2	0.344	0.340	0.337	0.331	0.342	0.318			
	t-statistics	1.47	1.38	1.27	1.08	1.41	0.15			
M2+	Pseudo-R^2	0.347	0.340	0.330	0.335	0.339	0.320			
	t-statistics	1.46	1.34	1.04	1.20	1.33	0.52			
M3	Pseudo-R^2	0.327	0.334	0.318	0.318	0.322	0.318			
	t-statistics	0.90	1.18	0.00	0.23	0.65	0.16			

TABLE A.5 (continued)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS FOUR-QUARTERS AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RM1	Pseudo-R^2	0.319	0.318	0.335	0.318	0.336	0.328			
	t-statistics	0.33	-0.15	1.20	0.15	1.25	0.94			
RM2	Pseudo-R^2	0.318	0.319	0.321	0.319	0.353	0.318			
	t-statistics	0.12	0.30	0.58	0.35	1.72	-0.10			
RM2+	Pseudo-R^2	0.318	0.318	0.318	0.319	0.352	0.318			
	t-statistics	0.03	0.12	0.21	0.38	1.68	0.28			
RM3	Pseudo-R^2	0.318	0.320	0.321	0.319	0.326	0.318			
	t-statistics	-0.13	0.46	-0.53	-0.35	0.87	-0.03			
MCI	Pseudo-R^2	0.274	0.267	0.264	0.263	0.258	0.253			
	t-statistics	1.57	1.30	1.17	1.12	0.77	-0.22			
RMCI	Pseudo-R^2	0.254	0.254	0.257	0.259	0.257	0.253			
	t-statistics	-0.38	0.31	0.71	0.85	0.70	-0.22			
PFX	Pseudo-R^2	0.258	0.262	0.264	0.253	0.254	0.264			
	t-statistics	0.84	-1.06	-1.19	-0.19	0.59	-1.18			
RPFX	Pseudo-R^2	0.253	0.261	0.258	0.253	0.260	0.264			
	t-statistics	0.19	-0.99	-0.78	-0.02	0.97	-1.18			
TSE	Pseudo-R^2	0.266	0.266	0.321	0.266	0.258	0.262			
	t-statistics	1.29	1.25	2.68*	1.18	0.85	1.09			
RTSE	Pseudo-R^2	0.260	0.261	0.321	0.260	0.258	0.260			
	t-statistics	0.95	1.03	2.49*	0.95	0.77	0.95			
DY	Pseudo-R^2	0.297	0.278	0.272	0.256	0.253	0.253			
	t-statistics	-2.08*	-1.65	-1.45	-0.63	-0.15	0.37			
PER	Pseudo-R^2	0.255	0.256	0.254	0.258	0.260	0.254			
	t-statistics	-0.63	-0.50	-0.49	-0.78	-0.87	-0.530			
SCLIS	Pseudo-R^2	0.264	0.271	0.271	0.261	0.253	0.286			
	t-statistics	1.15	1.45	1.49	0.97	0.12	1.86			
SCLINS	Pseudo-R^2	0.269	0.256	0.275	0.266	0.260	0.286			
	t-statistics	1.39	0.63	1.60	1.17	0.87	1.81			
FLI	Pseudo-R^2	0.274	0.254	0.256	0.254	0.258	0.263			
	t-statistics	1.57	0.29	0.49	0.03	0.63	0.66			
USRGDP	Pseudo-R^2	0.254	0.253	0.253	0.271	0.284	0.254			
	t-statistics	-0.46	-0.25	-0.21	1.46	1.90	-0.28			
USLI	Pseudo-R^2	0.261	0.253	0.253	0.253	0.253	0.253			
	t-statistics	0.99	-0.26	0.25	0.01	0.30	0.32			
USYC	Pseudo-R^2	0.289	0.287	0.285	0.260	0.253	0.253			
	t-statistics	-2.00*	-1.94	-1.89	-0.90	0.07	0.12			
DJI	Pseudo-R^2	0.253	0.253	0.261	0.253	0.254	0.253			
	t-statistics	0.34	0.05	1.03	0.35	0.40	-0.18			
SP500	Pseudo-R^2	0.254	0.253	0.269	0.261	0.261	0.256			
	t-statistics	0.41	0.21	1.40	1.02	0.99	0.60			
RSP500	Pseudo-R^2	0.254	0.253	0.269	0.261	0.261	0.256			
	t-statistics	0.41	0.21	1.40	1.02	0.99	0.60			

TABLE A.5 (end)
ESTIMATION RESULTS: TWO-VARIABLE PROBIT MODELS FOUR-QUARTERS AHEAD

		Lag *l*								
Variable X_t	**Statistics**	***l* = 0**	***l* = 1**	***l* = 2**	***l* = 3**	***l* = 4**	***l* = 5**	***l* = 6**	***l* = 7**	***l* = 11**
RLTCAUS	Pseudo-R^2	0.262	0.257	0.273	0.272	0.253	0.272			
	t-statistics	-1.06	-0.74	-1.49	-1.46	-0.09	-1.47			
RSTCAUS	Pseudo-R^2	0.283	0.269	0.295	0.272	0.260	0.258			
	t-statistics	-1.86	-1.15	-2.08*	-1.47	-0.94	-0.79			
USRYC	Pseudo-R^2	0.277	0.267	0.271	0.262	0.254	0.253			
	t-statistics	1.70	1.35	1.52	1.11	0.51	-0.02			
GERYC	Pseudo-R^2	0.340	0.325	0.282	0.256	0.256	0.255			
	t-statistics	-3.06*	-2.83*	-1.89	-0.62	0.67	0.35			
RGDP	Pseudo-R^2	0.253	0.257	0.262	0.258	0.270	0.253			
	t-statistics	-0.27	0.71	1.05	0.81	1.43	0.34			
ΔGBF	Pseudo-R^2	0.253	0.259	0.256	0.253	0.263	0.256			
	t-statistics	0.04	0.84	0.63	0.07	1.13	0.63			
ΔGRF	Pseudo-R^2	0.253	0.254	0.255	0.254	0.268	0.254			
	t-statistics	0.16	0.41	0.54	-0.30	1.36	0.42			
ΔGSF	Pseudo-R^2	0.253	0.258	0.255	0.253	0.253	0.255			
	t-statistics	0.18	-0.80	-0.53	-0.19	-0.29	-0.52			
CC	Pseudo-R^2	0.308	0.289	0.291	0.285	0.293	0.294			
	t-statistics	1.48	0.63	0.77	0.15	0.87	0.93			
ΔCC	Pseudo-R^2	0.320	0.285	0.302	0.301	0.289	0.287			
	t-statistics	1.83	-0.25	1.29	-1.25	-0.61	-0.43			
ΔSTOIR	Pseudo-R^2	0.253	0.257	0.272	0.254	0.260	0.264			
	t-statistics	0.15	0.67	1.49	0.31	0.84	0.81			

APPENDIX B

TABLE B.1
IN-SAMPLE PERFORMANCE OF THE PROBIT MODEL ONE-QUARTER AHEAD IN FORECASTING THE START OF A RECOVERY

Expansions	Lead or lag in forecasting the start of a recovery (in quarters)
1970	-1 (-2)
1975	0 (-1)
1980	0 (-1)
1983	0 (-1)
1991:	
- In-sample	0 (-1)
- Out-of-sample	0 (-1)

Note: The sign "-" indicates a lead and "+" a lag. The lead or lag is calculated with the 50 per cent probability rule. The lead or lag is the difference in quarters between the quarter in which the forecast probability of a recovery corresponds to and the actual start of a recovery. The number between parentheses are the warning lead or lag. The warning lead or lag is equal to the lead or lag minus the forecast horizon.